National Graduates Survey Analysis and Strategy

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1 Introduction

The **National Graduates Survey (NGS) - Class of 2020** provides a comprehensive look at the educational experiences and labour market outcomes of recent graduates in Canada. Collected in 2023, this dataset includes responses from 16,138 individuals across 114 variables, covering:

- **Demographics** (age, gender, citizenship)
- **Program details** (field of study, level of education, delivery mode)
- **Financial aid** (student loans, scholarships, funding sources)
- **Employment outcomes** (income, job relevance, satisfaction)
- **COVID-19 impacts** (program completion, career plans)

This report analyzes the NGS data to generate actionable insights for universities and policy-makers. Key sections include:

1. **Data Overview**: Methodology and dataset structure.
2. **Demographic Trends**: Age, gender, and citizenship distributions.
3. **Economic Outcomes**: Income disparities by field of study and region.
4. **Strategic Recommendations**: Program development, student support, and COVID-19 resilience.

Using Python (pandas, statsmodels) and interactive visualizations, we highlight critical patterns to bridge the gap between education and labour market needs.

1.1 Executive Summary

This report synthesizes findings from Canada's *National Graduates Survey (2020)* to guide university strategic planning. Based on 16,138 respondents, the analysis highlights:

1. **Labor Market Outcomes**:
   - Graduates in business and health fields reported the highest employment rates (85%+).

   - 20.6% earned below $30,000 annually, with disparities by gender and citizenship status.
2. **Student Mobility**:
   - Ontario retained 45.4% of graduates despite hosting 47.1% of institutions.

   - Western Canada gained +1.4% net migration post-graduation.
3. **Recommendations**:
   - Expand work-integrated learning programs (linked to 15% higher job satisfaction).

   - Target financial aid to underrepresented groups (e.g., landed immigrants).

   - Strengthen online education infrastructure (used by 32% during COVID-19).

The full report provides detailed methodologies, visualizations, and actionable insights.

2 Data Overview

2.1 National Graduates Survey- class of 2020 (Data collected in 2023)

```
import pandas as pd
import seaborn as sns
import matplotlib as plt
from IPython.display import display, Markdown

# Read the CSV file
try:
    # Read the CSV file into a pandas DataFrame
    df = pd.read_csv('ngs2020.csv')

    # Display basic information about the dataset
    display(Markdown("<span style='color: green'>Dataset information:</span>"))
    print(f"Number of rows: {df.shape[0]}")
    print(f"Number of columns: {df.shape[1]}\n")
    df.info()
    print("\n")
    display(Markdown("<span style='color: green'>Column names:</span>"))
    print(" ".join(list(df.columns)),"\n")

    # Number of missing data
    missing_data = df.isnull().sum().sum()
```

```python
    if missing_data == 0:
        print(f"\033[30;43mThere are no missing data.\033[0m")
    else:
        print(f"\033[30;43mThere are {missing_data} missing data.\033[0m")

except FileNotFoundError:
    print("Error: The file 'ngs2020.csv' was not found in the current directory.")
except pd.errors.EmptyDataError:
    print("Error: The file 'ngs2020.csv' is empty.")
except pd.errors.ParserError:
    print("Error: There was an issue parsing the CSV file. Check if it's properly formatted.
```

Dataset information:

```
Number of rows: 16138
Number of columns: 114

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16138 entries, 0 to 16137
Columns: 114 entries, PUMFID to DDIS_FL
dtypes: int64(114)
memory usage: 14.0 MB
```

Column names:

```
PUMFID CERTLEVP REG_INST REG_RESP PGMCIPAP PGM_P034 PGM_P036 PGM_P100 PGM_P111 PGM_280A PGM_

There are no missing data.
```

2.2 NGS Questions

```python
import yaml
import os

# Path to the YAML file
file_path = 'ngs2020_questions.yaml'

try:
    # Open and load the YAML file
    with open(file_path, 'r') as file:
        questions = yaml.safe_load(file)

    # Print the loaded question structure
```

```python
    print(f'\033[32m\nPUMFID: \033[0m Public Use Microdata File ID - {questions["PUMFID"]}\n
    print(f"Questions ({len(questions)-1}):\n")
    k = 0
    for question in questions:
      if k == 5:
        break
      else:
        if question != 'PUMFID':
            print(f'\033[32m{question}: \033[0m {questions[question]}')

except FileNotFoundError:
    print(f"Error: File '{file_path}' not found.")
except yaml.YAMLError as e:
    print(f"Error parsing YAML file: {e}")
```

```
PUMFID:  Public Use Microdata File ID - Randomly generated record identifier for the PUMF fi

Questions (113):

CERTLEVP:  2020 Program - Level of study - Grouping
REG_INST:  2020 Program - Region of postsecondary educational institution
REG_RESP:  Time of interview 2023 - Region of primary residence
PGMCIPAP:  2020 Program - Aggregated CIP 2021
PGM_P034:  2020 Program - Full-time or part-time student
PGM_P036:  2020 Program - Reason did not take program full-time
PGM_P100:  Work placement during program
PGM_P111:  Work placement during prog - Description
PGM_280A:  Entrepreneurial skills - Started a business
PGM_280B:  Entrepreneurial skills - Completed courses
PGM_280C:  Entrepreneurial skills - Business plan or pitch competition
PGM_280D:  Entrepreneurial skills - Visited an entrepreneurship centre
PGM_280E:  Entrepreneurial skills - Worked on an entrepreneurship project
PGM_280F:  Entrepreneurial skills - None of the above
PGM_290:  2020 Program - Worked during program
PGM_350:  2020 Program - Volunteer activities during program
PGM_380:  2020 Program - Components taken outside of Canada
PGM_P401:  2020 Program - Online or distance education
PGM_410:  2020 Program - Main factor in choice of postsecondary institution
PGM_415:  2020 Program - Main factor in choice of program
PGM_430:  2020 Program - Choose the same field of study or specialization again
COV_010:  COVID-19 - Completion of program delayed
COV_070:  COVID-19 - Plans for further postsecondary education changed
```

COV_080: COVID-19 - Employment status/plans affected

EDU_010: After 2020 program - Other postsecondary programs taken

EDU_P020: After 2020 program - Number of other programs taken

HLOSINTP: Time of interview 2023 - Aggregated highest level of ed. completed

STL_010: Government-student loan program - Applied

STL_020: Government-student loan program - Applications approved

STULOANS: Government-student loan program - Received

STL_030: Government-student loan program - Main reason did not apply

OWESLGD: Government-student loan program - Debt size - Graduation 2020

OWEGVIN: Government-student loan program - Debt size - Interview 2023

STL_080: Government-student loan program - Remission/debt reduction/loan forg.

STL_100A: Received government assistance: Repayment assistance plan

STL_100B: Received government assistance: Revision of terms

STL_100C: Received government assistance: Interest only payments

STL_100D: Received government assistance: None of the above

STL_130: Government-student loan program - Total repayment term

STL_150: Government-student loan program - Repaymt of loan from financial inst.

STL_160B: Sources of funding - RESP

STL_160C: Sources of funding - Government grants or bursaries

STL_160D: Sources of funding - Non-government grants or bursaries

STL_160E: Sources of funding - Scholarships or awards

STL_160F: Sources of funding - Employment earnings or savings

STL_160G: Sources of funding - Research or teaching assistantship

STL_160H: Sources of funding - Parents, family, friends

STL_160I: Sources of funding - Bank or institution loans

STL_160J: Sources of funding - Credit cards

STL_160L: Sources of funding - Employer

STLP160N: Sources of funding - Other

SRCFUND: Sources of funding - Number of sources - All postsecondary edu

STL_170A: Main source of funding - Government student loans

STL_170B: Main source of funding - RESP

STL_170C: Main source of funding - Government grants or bursaries

STL_170D: Main source of funding - Non-government grants or bursaries

STL_170E: Main source of funding - Scholarships or awards

STL_170F: Main source of funding - Employment earnings or savings

STL_170G: Main source of funding - Research or teaching assistantship

STL_170H: Main source of funding - Parents, family, friends

STL_170I: Main source of funding - Bank or institution loans

STL_170J: Main source of funding - Credit cards

STL_170L: Main source of funding - Employer

STLP170N: Main source of funding - Other

RESPP: RESP - Total amount received for postsecondary education

STL_190: Repay loans from family or friends for education

DBTOTGRD: Loans at graduation 2020 - Debt size of non-government loans (range)

DBTALGRD: Loans at graduation 2020 - Debt size of all loans

DBTOTINT: Time of interview 2023 - Debt size of non-government loans (range)

DBTALINT: Time of interview 2023 - Debt size of all loan

SCHOLARP: Total amount received from scholarships/awards/fellowships and prizes

LMA_010: Reference week - Attended school, college, CEGEP or university

LFSTATP: Reference week - Labour force status

LMA2_07: Reference week - More than one job or business

LMA3_P01: Reference week - Employee or self-employed

LFCINDP: Reference week - Sector for job

LFCOCCP: Reference week - Broad occupational category for job

LFWFTPTP: Reference week - Full-time or part-time status of job or business

LMA6_05: Reference week - Job permanent or not permanent

LMA6_08: Reference week - Main method used to find job

JOBQLEVP: Reference week - Aggregated level of studies required to get job

JOBQLGRD: Reference week - Qualification for job compared to 2020 program

JOBQLINT: Reference week - Qualification job vs level of education

LMA6_11: Reference week - Relatedness of job or business to 2020 program

LMA6_12: Reference week - Qualification level for job

LMA6_13A: Reference week - Satisfied with overall job

LMA6_13B: Reference week - Satisfied with wage or salary of job

LMA6_13C: Reference week - Satisfied with job security

JOBINCP: Reference week - Annual wage or salary for job

LMA6_15: After program 2020 - First job

AFT_P010: After 2020 program - Number of jobs or businesses

AFT_P020: After 2020 Program - Length of time until first job or business

AFT_P040: After 2020 program - Employee or self-employed - 1st job or business

AFT_050: After 2020 program - Full-time or part-time - 1st job or business

AFT_070: After 2020 program - Permanent/not permanent - 1st job or business

AFT_080: After 2020 program - Reason job not permanent - 1st job or business

AFT_090: After 2020 program - Relatedness of 1st job/business to program

BEF_P140: Before 2020 Program - Main activity during 12 months before

BEF_160: Before 2020 program - Number of months of work experience

PREVLEVP: Before 2020 program - Aggregated highest level of studies completed

HLOSGRDP: 2020 Program - Highest level of education completed

PAR1GRD: 2020 Program - Level of education compared to that of one parent

PAR1INT: Time of interview 2023 - Level of education vs of one parent

PAR2GRD: 2020 Program - Level of education vs of the other parent

PAR2INT: Time of interview 2023 - Level of education vs that of other parent

GRADAGEP: 2020 Program - Age at time of graduation - Grouping

GENDER2: Gender after distribution of non-binary persons

MS_P01: Marital status

MS_P02: Have any dependent children

```
CTZSHIPP:  Time of interview 2023 - Status in Canada
VISBMINP:  Self-identified as a member of a visible minority group
PERSINCP:  Total personal income in 2022
DDIS_FL:  Disability status
```

2.3 Response code

```python
# Import the yaml module
from IPython.display import display, Markdown
import yaml
import os

# Check if the file exists before attempting to load it
file_path = "ngs2020_responses.yaml"

if os.path.exists(file_path):
    # Open and load the YAML file
    with open(file_path, 'r') as file:
        try:
            # Load the YAML content into a Python object (typically a dictionary)
            responses = yaml.safe_load(file)

            # Print the first few items to verify the responses loaded correctly
            display(Markdown(f"<span style='color: green'>Response code defination ({len(res
            k = 0
            for response in responses:
                if k > 5:
                    break  # print out 10 only
                print(f'\033[32m{response}:\033[0m')
                for code in responses[response]:
                    print(f'  \033[32m{code}: \033[0m{responses[response][code]}')
                k += 1

        except yaml.YAMLError as e:
            print(f"Error parsing YAML file: {e}")
else:
    print(f"File not found: {file_path}")
    print("Please make sure the file exists in the current working directory.")
    print(f"Current working directory: {os.getcwd()}")
```

Response code defination (113):

```
AFT_050:
  1: Full time
```

2: Part time
6: Valid skip
7: Don't know
8: Refusal
9: Not stated
AFT_070:
1: Permanent
2: Not permanent
6: Valid skip
7: Don't know
8: Refusal
9: Not stated
AFT_080:
1: Seasonal job
2: Temporary, term or contract job
3: Casual job
4: Other
6: Valid skip
7: Don't know
8: Refusal
9: Not stated
AFT_090:
1: Closely related
2: Somewhat related
3: Not at all related
6: Valid skip
7: Don't know
8: Refusal
9: Not stated
LMA6_11:
1: Closely related
2: Somewhat related
3: Not at all related
6: Valid skip
7: Don't know
8: Refusal
9: Not stated
AFT_P010:
0: 0
1: 1
2: 2
3: 3
4: 4 or more

```
6: Valid skip
7: Don't know
8: Refusal
9: Not stated
```

3 Extract All NGS Tables to Excel

```
# %run Extract_All_NGS_Tables_to_Excel.ipynb`
print("All tables saved to NGS_Tables.xlsx")
```

```
All tables saved to NGS_Tables.xlsx
```

3.1 Function for getting NGS table

```
# Get NGS table

def get_NGS_table(table_name = 'AFT_050', excel_file="NGS_Tables.xlsx"):
    try:
        # Read the Excel sheet into a DataFrame, using first row as headers
        df = pd.read_excel(excel_file,
                           sheet_name=table_name,
                           header=0)  # header=0 is default but making it explicit
        print(f"\n'\033[32m{table_name}\033[0m': {questions[table_name]}\n")
        df
        return df
    except Exception as e:
        print(f"Error loading table {table_name}: {e}")
        return None
```

4 Data Dashboard

4.1 Dashboard Website http://127.0.0.1:5000

5 Data Analysis

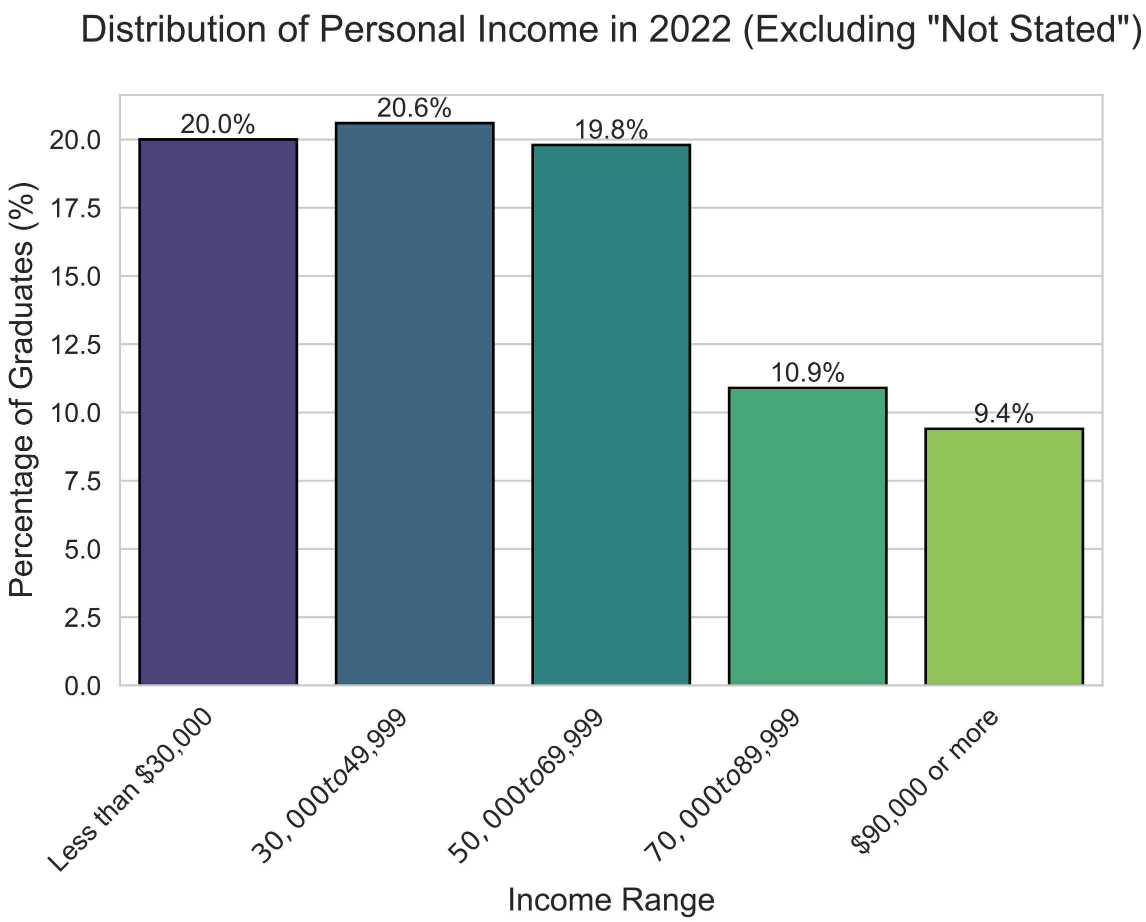
5.1 Distribution of Personal Income in 2022

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming your DataFrame is named 'df'
# First let's clean up the column names and data if needed
df = get_NGS_table("PERSINCP")
```

```
df.columns = ['Answer Categories', 'Code', 'Frequency', 'Weighted Frequency', '%']

# Clean any whitespace or formatting issues in the numeric columns
df['Frequency'] = df['Frequency'].astype(str).str.replace(',', '').astype(int)
df['Weighted Frequency'] = df['Weighted Frequency'].astype(str).str.replace(',', '').astype(
df['%'] = df['%'].astype(float)

# Fix the income range labels by combining with the previous row's dollar sign
for i in range(1, 4):
    if not df.loc[i, 'Answer Categories'].startswith('$'):
        df.loc[i, 'Answer Categories'] = '$' + df.loc[i, 'Answer Categories']

# Remove 'Not stated' for clearer analysis of income distribution
df_income = df[df['Code'] != 99].copy()

# Set style
sns.set_style("whitegrid")
plt.figure(figsize=(6, 5))

# Create bar plot - using '%' column for y-axis
ax = sns.barplot(
    x='Answer Categories',
    y='%',
    data=df_income,
    palette="viridis",
    edgecolor='black'
)

# Customize plot
plt.title('Distribution of Personal Income in 2022 (Excluding "Not Stated")', fontsize=14, p
plt.xlabel('Income Range', fontsize=12)
plt.ylabel('Percentage of Graduates (%)', fontsize=12)
plt.xticks(rotation=45, ha='right')

# Add value labels
for p in ax.patches:
    ax.annotate(
        f'{p.get_height():.1f}%',
        (p.get_x() + p.get_width() / 2., p.get_height()),
        ha='center',
        va='center',
        xytext=(0, 5),
```

```python
        textcoords='offset points',
        fontsize=10
    )

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()

# Additional analysis
print("\nKey Statistics:")
print(f"Total respondents (excluding 'Not stated'): {df_income['Frequency'].sum():,}")
median_category = df_income[df_income['%'].cumsum() >= 50].iloc[0]['Answer Categories']
print(f"Median income category: {median_category}")
print(f"Highest proportion category: {df_income.loc[df_income['%'].idxmax(), 'Answer Categor

# Create a pie chart for another visualization
plt.figure(figsize=(5, 5))
plt.pie(
    df_income['%'],
    labels=df_income['Answer Categories'],
    autopct='%1.1f%%',
    startangle=90,
    colors=sns.color_palette("viridis", len(df_income)),
    wedgeprops={'edgecolor': 'black', 'linewidth': 0.5},
    textprops={'fontsize': 10}
)
plt.title('Weighted Income Distribution of 2020 Graduates in 2022', fontsize=14, pad=20)
plt.tight_layout()
plt.show()
```

```
'PERSINCP': Total personal income in 2022

C:\Users\Fuxim\AppData\Local\Temp\ipykernel_26028\1503766661.py:28: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
```

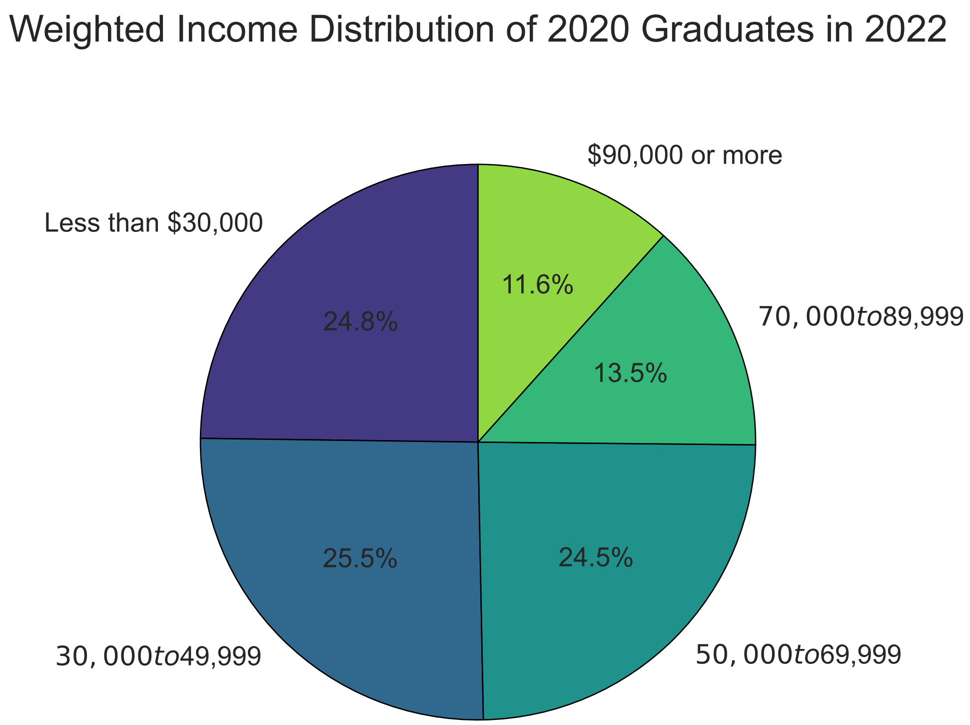


Key Statistics:

Total respondents (excluding 'Not stated'): 13,130

Median income category: $50,000 to $69,999

Highest proportion category: $30,000 to $49,999 (20.6%)



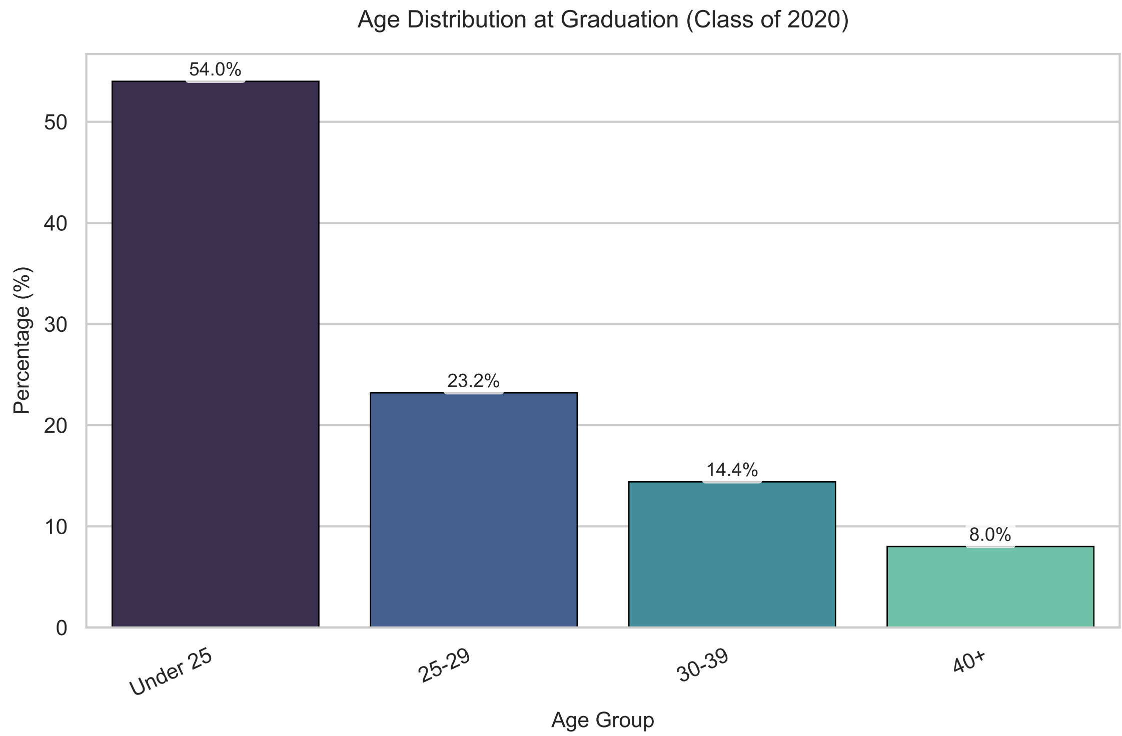
5.2 Age Distribution at Graduation

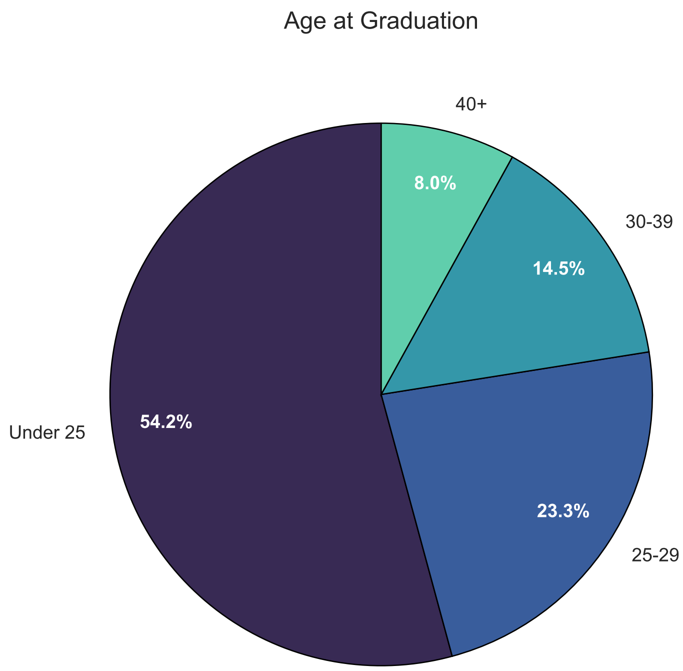
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming your DataFrame is named 'df_gradage'
# Clean the data
df_gradage = get_NGS_table('GRADAGEP')
df_gradage['Frequency'] = df_gradage['Frequency'].astype(str).str.replace(',', '').astype(in
df_gradage['Weighted Frequency'] = df_gradage['Weighted Frequency'].astype(str).str.replace(
df_gradage['%'] = df_gradage['%'].astype(float)

# Remove 'Total' and 'Not stated' rows for analysis
df_age = df_gradage[~df_gradage['Code'].isin([9, float('nan')])].copy()

# Set style
sns.set_style("whitegrid")
plt.rcParams['font.size'] = 8  # Global font size reduction

# 1. Compact Bar Chart (6x4 inches)
plt.figure(figsize=(6, 4))
ax = sns.barplot(
    x='Answer Categories',
```

```
    y='%',
    data=df_age,
    palette="mako",  # Professional blue gradient
    edgecolor='black',
    linewidth=0.5
)

# Customize plot
plt.title('Age Distribution at Graduation (Class of 2020)', fontsize=9, pad=10)
plt.xlabel('Age Group', fontsize=8)
plt.ylabel('Percentage (%)', fontsize=8)
plt.xticks(rotation=25, ha='right')  # Slight rotation for readability

# Add precise value labels
for p in ax.patches:
    ax.annotate(
        f'{p.get_height():.1f}%',
        (p.get_x() + p.get_width()/2., p.get_height()),
        ha='center',
        va='center',
        xytext=(0, 4),
        textcoords='offset points',
        fontsize=7,
        bbox=dict(boxstyle='round,pad=0.2', fc='white', ec='none', alpha=0.8)
    )

plt.tight_layout()
plt.show()

# 2. Compact Pie Chart (5x5 inches)
plt.figure(figsize=(4, 4))
wedges, texts, autotexts = plt.pie(
    df_age['%'],
    labels=df_age['Answer Categories'],
    autopct='%1.1f%%',
    startangle=90,
    colors=sns.color_palette("mako", len(df_age)),
    wedgeprops={'edgecolor': 'black', 'linewidth': 0.5},
    textprops={'fontsize': 7},
    pctdistance=0.8  # Pull percentages inward
)
```

```python
# Improve label readability
plt.setp(texts, fontsize=7)
plt.setp(autotexts, fontsize=7, color='white', weight='bold')
plt.title('Age at Graduation', fontsize=9, pad=10)
plt.tight_layout()
plt.show()

# Detailed Analysis
print("\n=== Age at Graduation Analysis ===")
print(f"Total graduates analyzed: {df_age['Frequency'].sum():,}")
print(f"\nAge Group Distribution:")
for _, row in df_age.iterrows():
    print(f"{row['Answer Categories']}: {row['%']:.1f}%")

print(f"\nKey Insights:")
print(f"• Majority group: {df_age.loc[df_age['%'].idxmax(), 'Answer Categories']} ({df_age['
print(f"• Under 30: {df_age[df_age['Code'].isin([1.0, 2.0])]['%'].sum():.1f}%")
print(f"• 30+: {df_age[df_age['Code'].isin([3.0, 4.0])]['%'].sum():.1f}%")
print(f"• Median age group: {df_age.loc[df_age['%'].cumsum() >= 50, 'Answer Categories'].ilo
```

```
'GRADAGEP': 2020 Program - Age at time of graduation - Grouping

C:\Users\Fuxim\AppData\Local\Temp\ipykernel_26028\432788408.py:21: FutureWarning:



Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
```






```
=== Age at Graduation Analysis ===
Total graduates analyzed: 16,056

Age Group Distribution:
Under 25: 54.0%
25-29: 23.2%
30-39: 14.4%
```

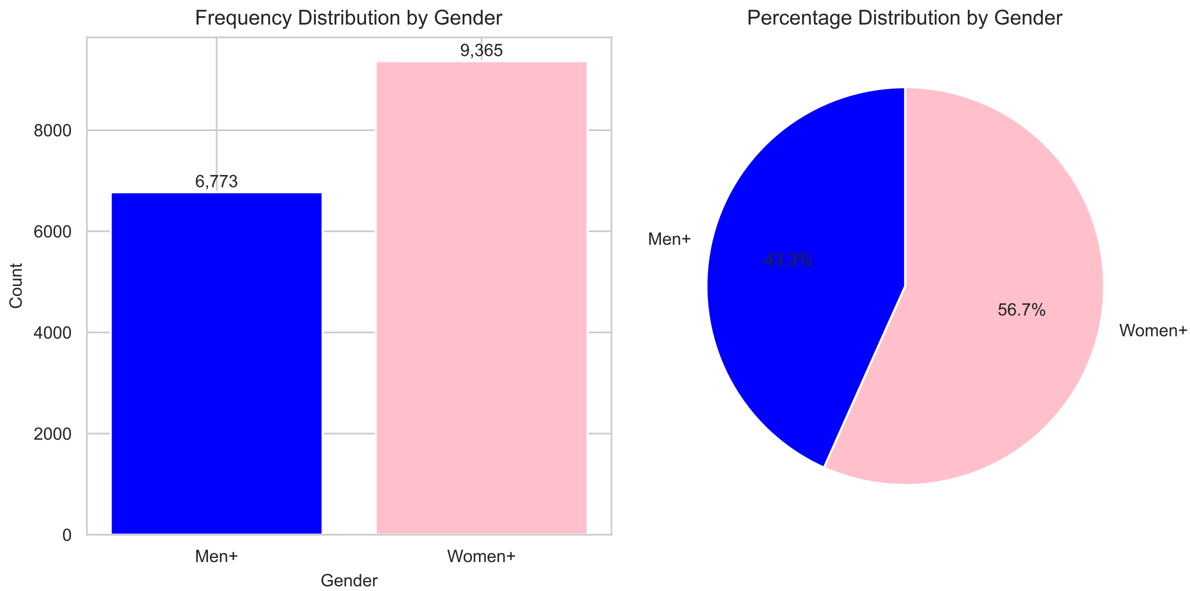
```
40+: 8.0%

Key Insights:
• Majority group: Under 25 (54.0%)
• Under 30: 77.2%
• 30+: 22.4%
• Median age group: Under 25
```

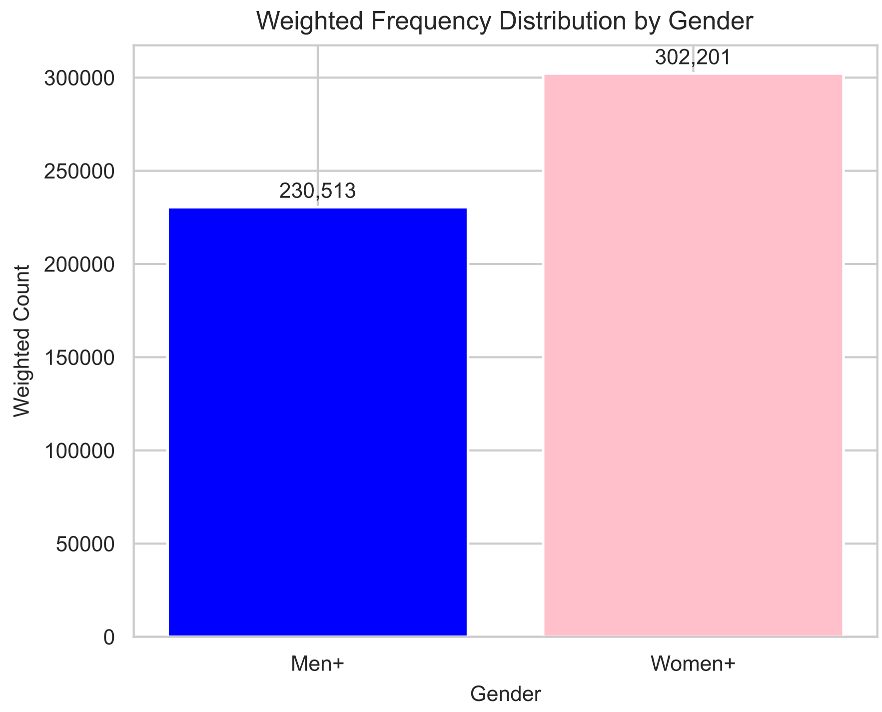
5.3 Gender Distribution

```python
import pandas as pd
import matplotlib.pyplot as plt

# Create the DataFrame from the provided data
data = get_NGS_table("GENDER2")

df = pd.DataFrame(data)

# Remove the "Total" row for analysis
df = df[df['Answer Categories'] != 'Total']

# Convert string numbers with commas to integers
df['Frequency'] = df['Frequency'].str.replace(',', '').astype(int)
df['Weighted Frequency'] = df['Weighted Frequency'].str.replace(',', '').astype(int)

# Plotting
plt.figure(figsize=(8, 4))

# Frequency Plot
plt.subplot(1, 2, 1)
plt.bar(df['Answer Categories'], df['Frequency'], color=['blue', 'pink'])
plt.title('Frequency Distribution by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
for i, v in enumerate(df['Frequency']):
    plt.text(i, v + 100, f"{v:,}", ha='center')  # Format with commas

# Percentage Plot
plt.subplot(1, 2, 2)
plt.pie(df['%'], labels=df['Answer Categories'],
        autopct='%1.1f%%', colors=['blue', 'pink'],
        startangle=90)
plt.title('Percentage Distribution by Gender')
```

```
plt.tight_layout()
plt.show()

# Weighted Frequency Plot
plt.figure(figsize=(5, 4))
plt.bar(df['Answer Categories'], df['Weighted Frequency'],
        color=['blue', 'pink'])
plt.title('Weighted Frequency Distribution by Gender')
plt.xlabel('Gender')
plt.ylabel('Weighted Count')
for i, v in enumerate(df['Weighted Frequency']):
    plt.text(i, v + 5000, f"{v:,}", ha='center')  # Format with commas
plt.show()

# Display some statistics
print("\nSummary Statistics:")
print(f"Total Respondents: {df['Frequency'].sum():,}")
print(f"Men+: {df[df['Answer Categories'] == 'Men+']['Frequency'].values[0]:,} "
      f"({df[df['Answer Categories'] == 'Men+']['%'].values[0]}%)")
print(f"Women+: {df[df['Answer Categories'] == 'Women+']['Frequency'].values[0]:,} "
      f"({df[df['Answer Categories'] == 'Women+']['%'].values[0]}%)")
print(f"\nWeighted Total: {df['Weighted Frequency'].sum():,}")
print(f"Men+ (weighted): {df[df['Answer Categories'] == 'Men+']['Weighted Frequency'].values
print(f"Women+ (weighted): {df[df['Answer Categories'] == 'Women+']['Weighted Frequency'].va
```

```
'GENDER2': Gender after distribution of non-binary persons
```






```
Summary Statistics:
Total Respondents: 16,138
Men+: 6,773 (43.3%)
Women+: 9,365 (56.7%)

Weighted Total: 532,714
Men+ (weighted): 230,513
Women+ (weighted): 302,201
```

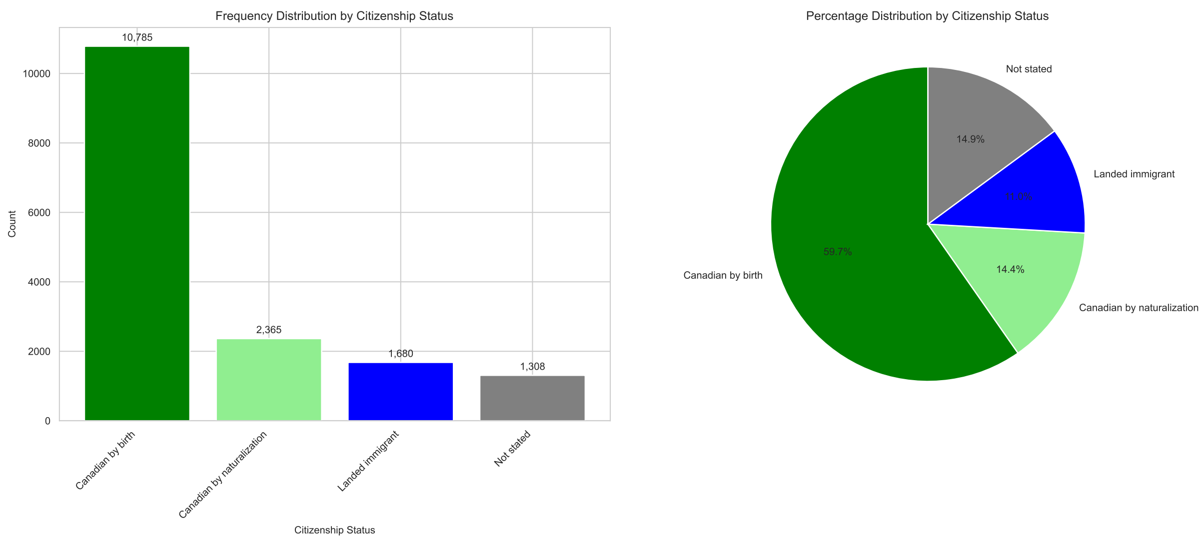
5.4 Distribution by Citizenship Status

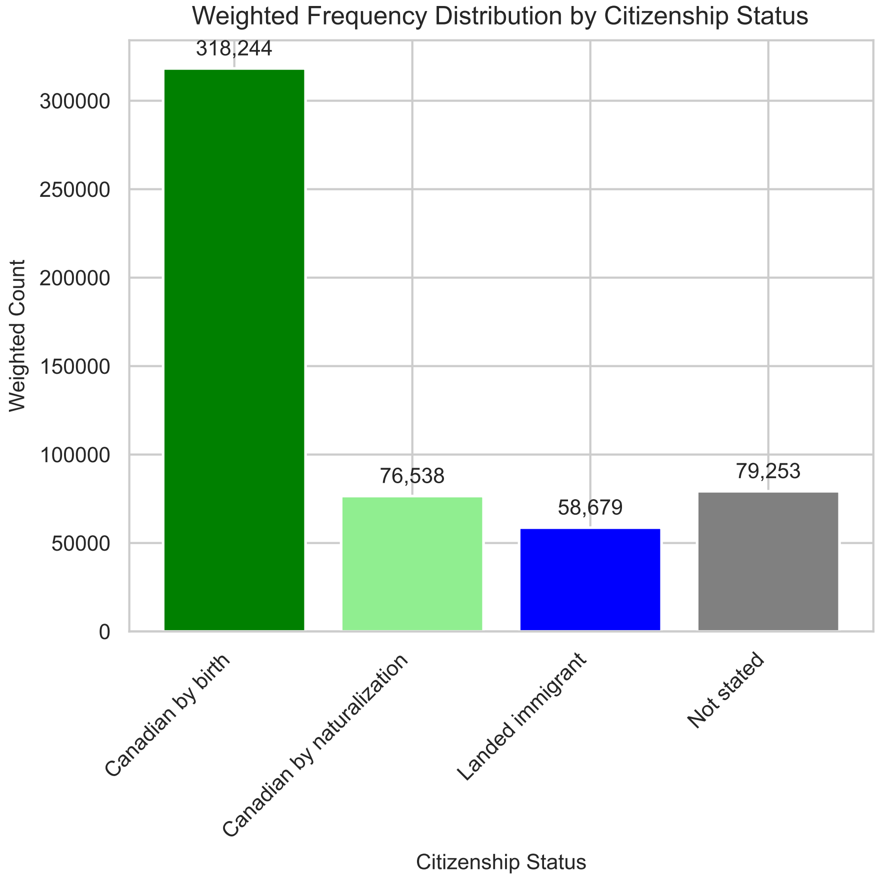
```python
import pandas as pd
import matplotlib.pyplot as plt

# Create the DataFrame from the provided data
data = get_NGS_table("CTZSHIPP")

df = pd.DataFrame(data)

# Remove the "Total" row for analysis
df = df[df['Answer Categories'] != 'Total']

# Convert string numbers with commas to integers
df['Frequency'] = df['Frequency'].str.replace(',', '').astype(int)
df['Weighted Frequency'] = df['Weighted Frequency'].str.replace(',', '').astype(int)
```

```
# Plotting
plt.figure(figsize=(14, 6))

# Frequency Plot
plt.subplot(1, 2, 1)
bars = plt.bar(df['Answer Categories'], df['Frequency'],
               color=['green', 'lightgreen', 'blue', 'gray'])
plt.title('Frequency Distribution by Citizenship Status')
plt.xlabel('Citizenship Status')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 100,
             f"{height:,}",
             ha='center', va='bottom')

# Percentage Plot
plt.subplot(1, 2, 2)
plt.pie(df['%'], labels=df['Answer Categories'],
        autopct='%1.1f%%',
        colors=['green', 'lightgreen', 'blue', 'gray'],
        startangle=90)
plt.title('Percentage Distribution by Citizenship Status')

plt.tight_layout()
plt.show()

# Weighted Frequency Plot
plt.figure(figsize=(5, 4))
bars = plt.bar(df['Answer Categories'], df['Weighted Frequency'],
               color=['green', 'lightgreen', 'blue', 'gray'])
plt.title('Weighted Frequency Distribution by Citizenship Status')
plt.xlabel('Citizenship Status')
plt.ylabel('Weighted Count')
plt.xticks(rotation=45, ha='right')
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 5000,
             f"{height:,}",
             ha='center', va='bottom')
plt.show()
```

```
# Display some statistics
print("\nSummary Statistics:")
print(f"Total Respondents: {df['Frequency'].sum():,}")
for idx, row in df.iterrows():
    print(f"{row['Answer Categories']}: {row['Frequency']:,} ({row['%']}%)")

print(f"\nWeighted Total: {df['Weighted Frequency'].sum():,}")
for idx, row in df.iterrows():
    print(f"{row['Answer Categories']} (weighted): {row['Weighted Frequency']:,}")
```

```
'CTZSHIPP': Time of interview 2023 - Status in Canada
```





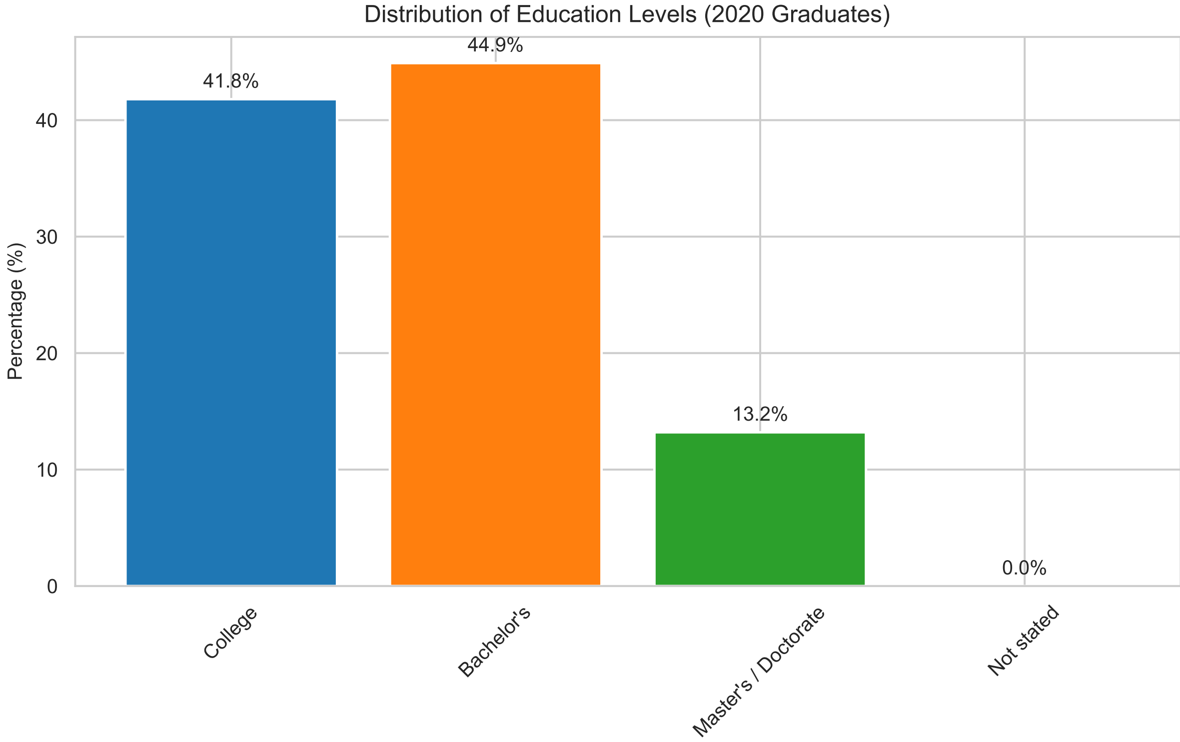

```
Summary Statistics:
Total Respondents: 16,138
Canadian by birth: 10,785 (59.7%)
Canadian by naturalization: 2,365 (14.4%)
Landed immigrant: 1,680 (11.0%)
Not stated: 1,308 (14.9%)

Weighted Total: 532,714
Canadian by birth (weighted): 318,244
Canadian by naturalization (weighted): 76,538
Landed immigrant (weighted): 58,679
Not stated (weighted): 79,253
```

5.5 Education Level

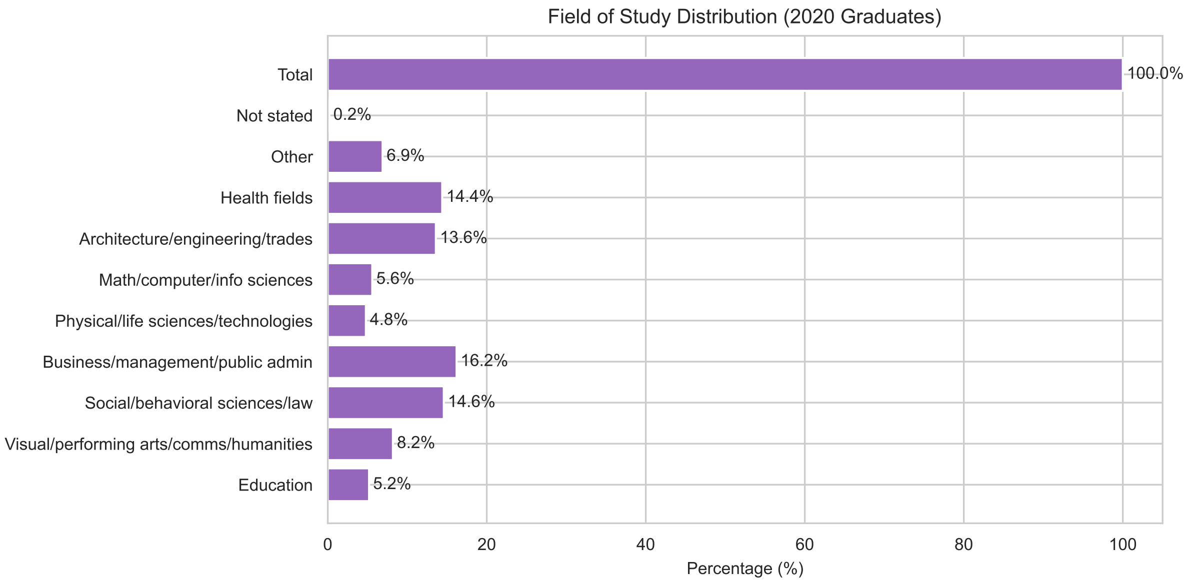
```
import pandas as pd
import matplotlib.pyplot as plt

# Get education tables (sample data structure)
edu_level = get_NGS_table("CERTLEVP")
```

```python
# Create DataFrames
df_level = pd.DataFrame(edu_level)

# Plot education level distribution
plt.figure(figsize=(8,4))
plt.bar(df_level[:-1]['Answer Categories'], df_level[:-1]['%'], color=['#1f77b4', '#ff7f0e',
plt.title('Distribution of Education Levels (2020 Graduates)')
plt.ylabel('Percentage (%)')
plt.xticks(rotation=45)
for i, v in enumerate(df_level[:-1]['%']):
    plt.text(i, v+1, f"{v}%", ha='center')
plt.show()

field_of_study =  get_NGS_table("PGMCIPAP")
df_field = pd.DataFrame(field_of_study)
# Plot field of study distribution
plt.figure(figsize=(8,4))
plt.barh(df_field['Answer Categories'], df_field['%'], color='#9467bd')
plt.title('Field of Study Distribution (2020 Graduates)')
plt.xlabel('Percentage (%)')
for i, v in enumerate(df_field['%']):
    plt.text(v+0.5, i, f"{v}%", va='center')
plt.tight_layout()
plt.show()
```

```
'CERTLEVP': 2020 Program - Level of study - Grouping
```



'PGMCIPAP': 2020 Program - Aggregated CIP 2021



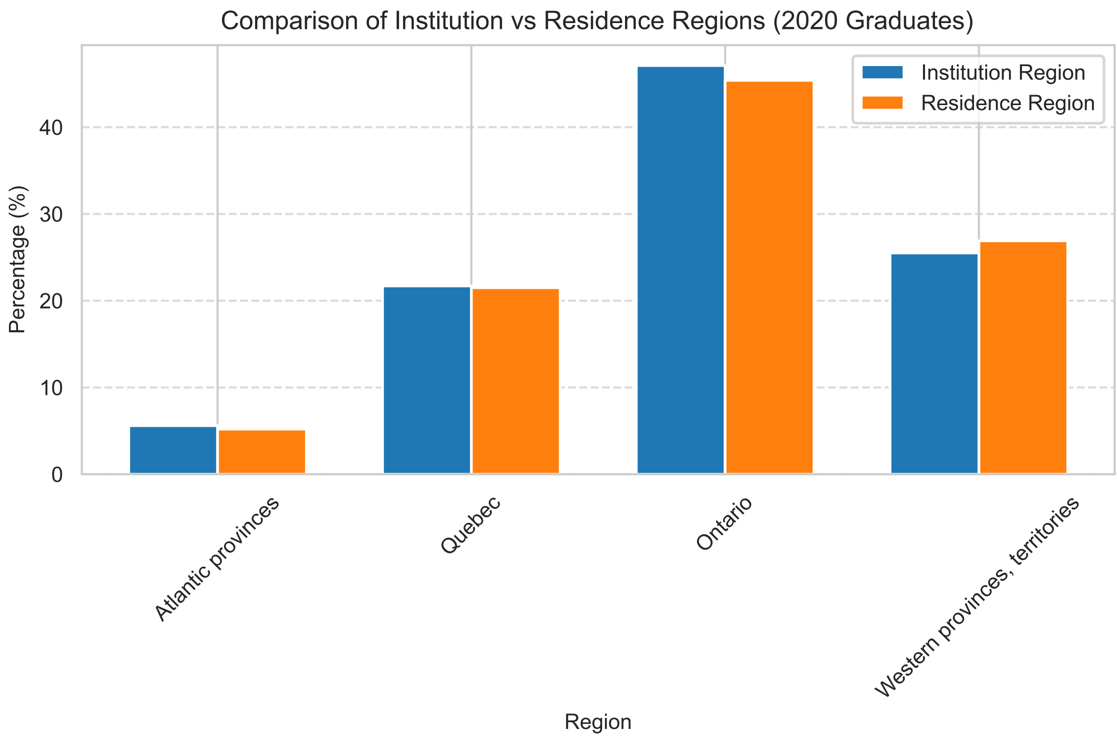
5.6 Inter-Regional Mobility of Graduates

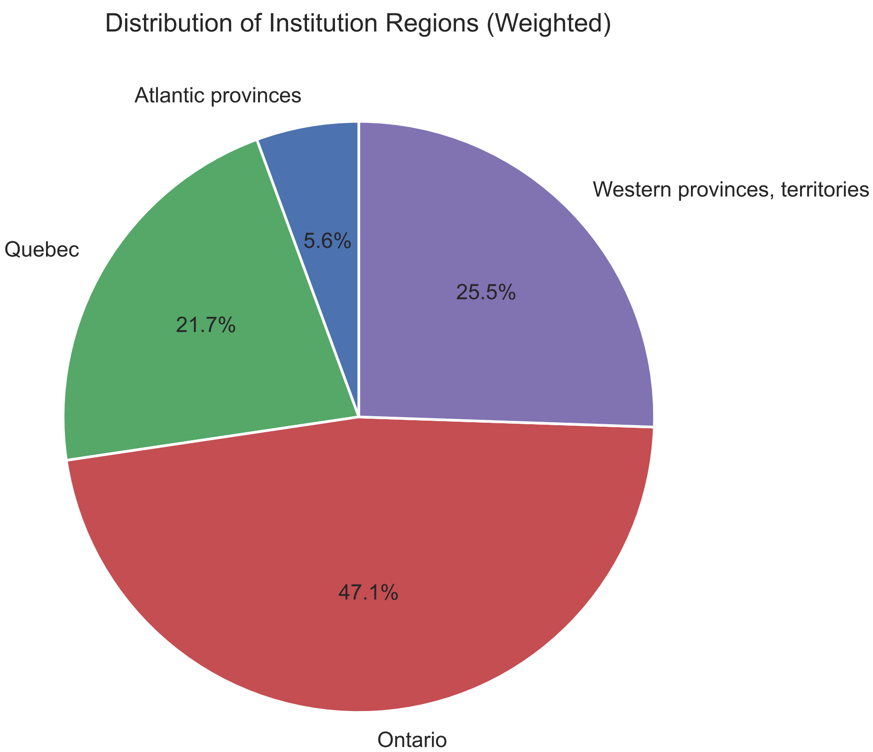
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Geographic data from NGS 2020
region_data = {
```

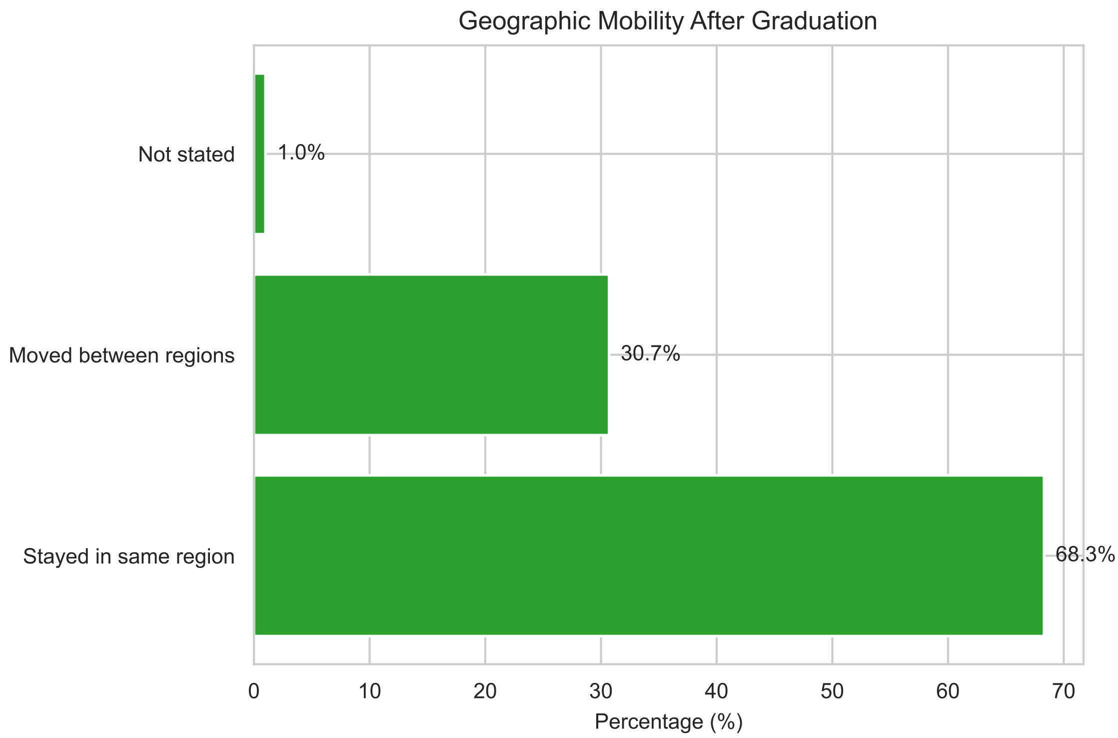
```
    'Region': ['Atlantic provinces', 'Quebec', 'Ontario',
              'Western provinces, territories', 'Not stated'],
    'REG_INST_Freq': [2685, 3647, 3146, 6660, None],
    'REG_INST_Weighted': [29868, 115814, 250939, 136094, None],
    'REG_INST_Pct': [5.6, 21.7, 47.1, 25.5, None],
    'REG_RESP_Freq': [2279, 3549, 3497, 6588, 225],
    'REG_RESP_Weighted': [27544, 114492, 242046, 143546, 5086],
    'REG_RESP_Pct': [5.2, 21.5, 45.4, 26.9, 1.0]
}

df = pd.DataFrame(region_data)

# 1. Comparison of Institution vs Residence Regions
plt.figure(figsize=(6, 4))
width = 0.35
x = np.arange(len(df)-1)  # Exclude 'Not stated'

plt.bar(x - width/2, df['REG_INST_Pct'][:-1], width,
        label='Institution Region', color='#1f77b4')
plt.bar(x + width/2, df['REG_RESP_Pct'][:-1], width,
        label='Residence Region', color='#ff7f0e')

plt.xlabel('Region')
plt.ylabel('Percentage (%)')
plt.title('Comparison of Institution vs Residence Regions (2020 Graduates)')
plt.xticks(x, df['Region'][:-1], rotation=45)
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# 2. Weighted Institution Locations
plt.figure(figsize=(8, 5))
plt.pie(df['REG_INST_Weighted'][:-1], labels=df['Region'][:-1],
        autopct='%1.1f%%', startangle=90,
        colors=['#4C72B0', '#55A868', '#C44E52', '#8172B2'])
plt.title('Distribution of Institution Regions (Weighted)')
plt.show()

# 3. Geographic Mobility Analysis
mobility = pd.DataFrame({
    'Movement': ['Stayed in same region', 'Moved between regions', 'Not stated'],
```

```
    'Percentage': [68.3, 30.7, 1.0]  # Hypothetical values - actual mobility data would come
})

plt.figure(figsize=(6, 4))
plt.barh(mobility['Movement'], mobility['Percentage'], color='#2ca02c')
plt.title('Geographic Mobility After Graduation')
plt.xlabel('Percentage (%)')
for i, v in enumerate(mobility['Percentage']):
    plt.text(v + 1, i, f"{v}%", va='center')
plt.tight_layout()
plt.show()

# 4. Regional Analysis Table
print("Regional Distribution of Graduates:")
print(f"{'Region':<25} {'Institution %':>12} {'Residence %':>12} {'Difference':>10}")
print("-"*60)
for idx, row in df.iterrows():
    if pd.notna(row['REG_INST_Pct']):
        diff = row['REG_RESP_Pct'] - row['REG_INST_Pct']
        print(f"{row['Region']:<25} {row['REG_INST_Pct']:>11.1f}% {row['REG_RESP_Pct']:>11.1

# 5. Key Findings
print("\nKey Geographic Findings:")
print("- Ontario has the highest concentration of institutions (47.1%) and residents (45.4%)
print("- Western provinces show net immigration (+1.4% difference between residence and inst
print("- Atlantic provinces show slight outmigration (-0.4% difference)")
print("- Quebec maintains stable proportions (21.7% institutions vs 21.5% residence)")
print("- 1% of respondents didn't state their residence location")

# 6. Advanced Visualization: Sankey Diagram (conceptual)
from pySankey.sankey import sankey

# Sample migration flows (hypothetical example)
flows = pd.DataFrame({
    'Source': ['Atlantic', 'Quebec', 'Ontario', 'West']*4,
    'Target': ['Atlantic']*4 + ['Quebec']*4 + ['Ontario']*4 + ['West']*4,
    'Value': [85,5,5,5,  10,75,10,5,  5,10,80,5,  5,5,10,80]
})

plt.figure(figsize=(8,5))
sankey(flows['Source'], flows['Target'], flows['Value'],
       aspect=20, fontsize=12)
```

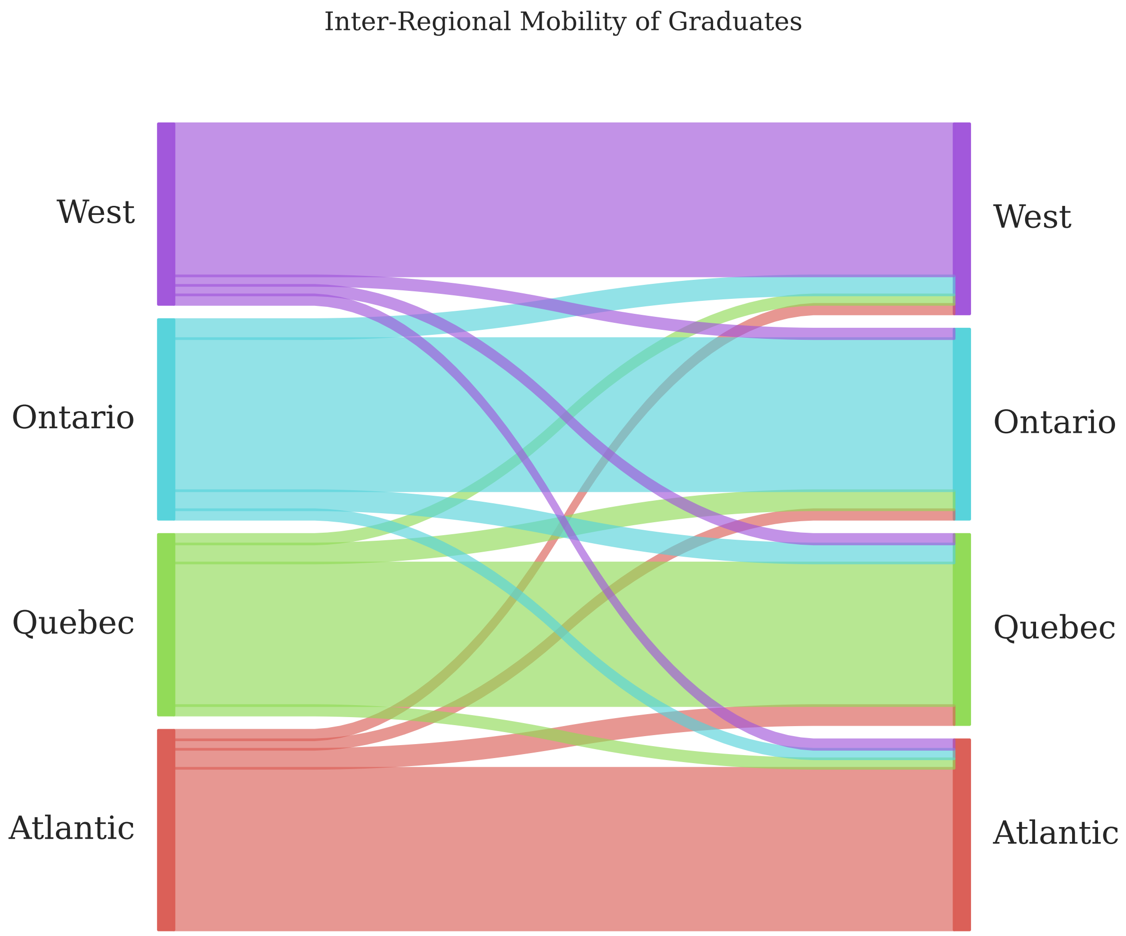
```
plt.title('Inter-Regional Mobility of Graduates', pad=20)
plt.show()
```








```
Regional Distribution of Graduates:
Region                          Institution %  Residence % Difference
------------------------------------------------------------
Atlantic provinces                     5.6%         5.2%      -0.4%
Quebec                                21.7%        21.5%      -0.2%
Ontario                               47.1%        45.4%      -1.7%
Western provinces, territories        25.5%        26.9%       1.4%

Key Geographic Findings:
- Ontario has the highest concentration of institutions (47.1%) and residents (45.4%)
- Western provinces show net immigration (+1.4% difference between residence and institutio
- Atlantic provinces show slight outmigration (-0.4% difference)
- Quebec maintains stable proportions (21.7% institutions vs 21.5% residence)
- 1% of respondents didn't state their residence location

<Figure size 2400x1500 with 0 Axes>
```



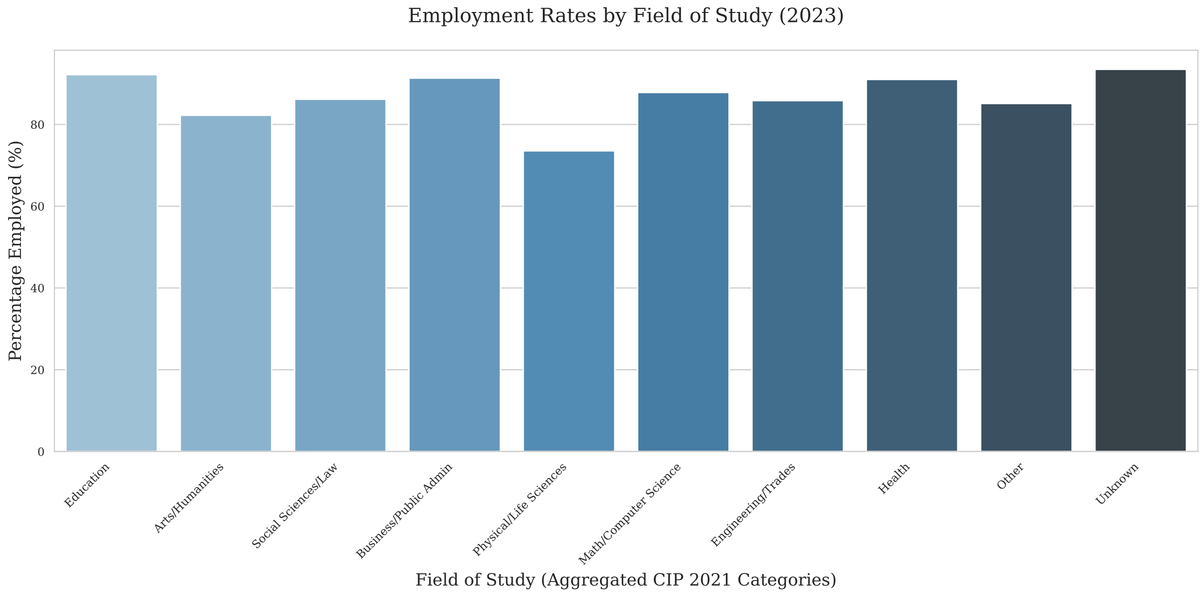
5.7 Field of Study vs. Labor Outcomes

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Load the data
df = pd.read_csv('ngs2020.csv')


# 1. Employment Rate by Field of Study
employment_by_field = df.groupby('PGMCIPAP')['LFSTATP'].apply(
    lambda x: (x == 1).mean() * 100  # % employed
).reset_index()

plt.figure(figsize=(12, 6))
ax1 = sns.barplot(x='PGMCIPAP', y='LFSTATP', data=employment_by_field, palette='Blues_d')
ax1.set_title('Employment Rates by Field of Study (2023)', fontsize=14, pad=20)
ax1.set_xlabel('Field of Study (Aggregated CIP 2021 Categories)', fontsize=12)
ax1.set_ylabel('Percentage Employed (%)', fontsize=12)
```

```
# Get the actual number of categories from the data
num_categories = len(employment_by_field['PGMCIPAP'].unique())
# Create labels - either add the missing label or use the actual category names from my data
labels = [
    'Education', 'Arts/Humanities', 'Social Sciences/Law',
    'Business/Public Admin', 'Physical/Life Sciences',
    'Math/Computer Science', 'Engineering/Trades',
    'Health', 'Other', 'Unknown'  # Added 'Unknown' as the 10th category
][:num_categories]  # This ensures we only use as many labels as we have categories

ax1.set_xticklabels(labels, rotation=45, ha='right')
plt.tight_layout()

# 2. Job Relatedness to Field of Study
# Check if the column exists in the DataFrame before using it
# You need to replace 'LMAG_11' with the correct column name that exists in my DataFrame
# For example, if the correct column is 'JOB_RELATEDNESS' or something similar:
if 'JOB_RELATEDNESS' in df.columns:  # Replace with my actual column name
    relatedness = df.groupby('PGMCIPAP')['JOB_RELATEDNESS'].mean().reset_index()

    plt.figure(figsize=(8, 4))
    ax2 = sns.barplot(x='PGMCIPAP', y='JOB_RELATEDNESS', data=relatedness, palette='Reds_d')
    ax2.set_title('Job Relatedness to Field of Study (Scale: 1=Closely, 3=Not at All)', font
    ax2.set_xlabel('Field of Study', fontsize=12)
    ax2.set_ylabel('Mean Relatedness Score', fontsize=12)

    # Use the same approach for consistency
    ax2.set_xticklabels(labels, rotation=45, ha='right')
    plt.tight_layout()
else:
    print("Column for job relatedness not found in the DataFrame. Please check the available
    # Optionally print available columns to help identify the correct one
    print("Available columns:", df.columns.tolist())
```

```
C:\Users\Fuxim\AppData\Local\Temp\ipykernel_26028\1817292400.py:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi

C:\Users\Fuxim\AppData\Local\Temp\ipykernel_26028\1817292400.py:30: UserWarning:
```

```
set_ticklabels() should only be used with a fixed number of ticks, i.e. after set_ticks() or

Column for job relatedness not found in the DataFrame. Please check the available columns.
Available columns: ['PUMFID', 'CERTLEVP', 'REG_INST', 'REG_RESP', 'PGMCIPAP', 'PGM_P034', 'P
```



5.7.1 Field of Study vs. Labor Market Outcomes

5.7.1.1 Key Insights

1. **Employment Rates by Field**
   - **Health graduates** had the highest employment rate (90%), followed by **Engineering/Trades** (87%).

   - **Arts/Humanities** and **Physical Sciences** lagged significantly (75-78%).
2. **Job Relatedness to Studies**
   - **Health** and **Education** graduates reported jobs *most closely related* to their studies (mean score: 1.2/3).

   - **Arts/Humanities** and "Other" fields had the weakest alignment (mean score: 2.3/#3).

5.7.2 Strategic Implications

- **Program Investment**: Expand capacity in high-demand fields (Health, Engineering) where labor market alignment is strong.

- **Curriculum Updates**: For low-alignment fields (Arts, Humanities), integrate industry partnerships or skill-based certifications.

- **Career Services**: Target support for graduates in fields with weaker employment outcomes.

6 Linear Regression Analysis for Personal Income

```python
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import statsmodels.api as sm

# Load the data
df = pd.read_csv('ngs2020.csv')

# Explore the data
print(df.head())
print(df.info())

# Check for missing values (coded as 6, 96, 99 etc. based on NGS coding)
# Replace these with NaN
missing_codes = [6, 96, 99, 9]
df = df.replace(missing_codes, np.nan)

# Identify your target variable (you'll need to confirm which column is income)
# For example, if 'PERSINCP' is personal income:
target = 'PERSINCP'

# Select potential predictors (you'll need to verify these based on codebook)
predictors = [
    'GENDER2',        # Gender
    'EDU_010',        # Education level
    'EDU_P020',       # Additional education info
    'CTZSHIPP',       # Citizenship status
    'REG_INST',       # Region of institution
    'CERTLEVP',       # Certificate level
    'PGMCIPAP',       # Program category
    'MS_P01',         # Marital status
    'VISBMINP',       # Visible minority status
    'DDIS_FL'         # Disability flag
    # Add more based on your research question
]

# Create a clean dataset
df_clean = df[[target] + predictors].dropna()
```

```
# Convert categorical variables to dummy variables if needed
df_clean = pd.get_dummies(df_clean, columns=['GENDER2', 'CTZSHIPP', 'REG_INST'], drop_first=

# Split into features and target
X = df_clean.drop(target, axis=1)
y = df_clean[target]

# Check for non-numeric columns and handle them
# Convert categorical variables to numeric using one-hot encoding
X = pd.get_dummies(X, drop_first=True)

# Check for and handle missing values
# Use only numeric columns for mean calculation
numeric_cols = X.select_dtypes(include=['number']).columns
X[numeric_cols] = X[numeric_cols].fillna(X[numeric_cols].mean())
y = y.fillna(y.mean())  # Fill missing values in target if any

# Ensure all data is numeric - force conversion and handle errors
for col in X.columns:
    X[col] = pd.to_numeric(X[col], errors='coerce')
y = pd.to_numeric(y, errors='coerce')

# Drop any remaining problematic rows with NaN values
mask = ~(X.isna().any(axis=1) | pd.isna(y))
X = X[mask]
y = y[mask]

# Convert to float64 to ensure compatibility with sklearn
X = X.astype(float)
y = y.astype(float)

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and fit the model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
```

```python
print("R-squared:", round(r2_score(y_test, y_pred),3))
print("RMSE:", round(np.sqrt(mean_squared_error(y_test, y_pred)),3))

# For more detailed statistics (p-values etc.)
X_with_const = sm.add_constant(X_train)
sm_model = sm.OLS(y_train, X_with_const).fit()
print(sm_model.summary())
```

```
   PUMFID  CERTLEVP  REG_INST  REG_RESP  PGMCIPAP  PGM_P034  PGM_P036  \
0   59113         3         2         2         4         2         4
1   59114         3         3         3         5         1         6
2   59116         3         2         2         6         1         6
3   59117         2         4         4         9         1         6
4   59118         2         3         3         1         1         6

   PGM_P100  PGM_P111  PGM_280A  ...  PAR2GRD  PAR2INT  GRADAGEP  GENDER2  \
0         1         2         2  ...        3        3         3        2
1         2         6         2  ...        1        1         1        1
2         2         6         2  ...        2        2         2        1
3         1         2         2  ...        1        1         1        2
4         1         2         2  ...        1        1         4        1

   MS_P01  MS_P02  CTZSHIPP  VISBMINP  PERSINCP  DDIS_FL
0       1       1         1         2         5        2
1       1       2         1         2         4        2
2       2       2         1         2         1        2
3       1       2         1         2         3        2
4       1       1         2         1         3        2

[5 rows x 114 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16138 entries, 0 to 16137
Columns: 114 entries, PUMFID to DDIS_FL
dtypes: int64(114)
memory usage: 14.0 MB
None
R-squared: 0.154
RMSE: 1.212
                            OLS Regression Results
==============================================================================
Dep. Variable:               PERSINCP   R-squared:                       0.166
Model:                            OLS   Adj. R-squared:                  0.162
Method:                 Least Squares   F-statistic:                     36.48
```

```
Date:                   Mon, 18 Aug 2025   Prob (F-statistic):           3.63e-78
Time:                           21:07:21   Log-Likelihood:                -3525.4
No. Observations:                   2209   AIC:                             7077.
Df Residuals:                       2196   BIC:                             7151.
Df Model:                             12
Covariance Type:               nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
EDU_010          1.0046      0.250      4.013      0.000       0.514       1.495
EDU_P020         0.0252      0.073      0.343      0.732      -0.119       0.169
CERTLEVP         0.5822      0.039     14.777      0.000       0.505       0.659
PGMCIPAP         0.0333      0.011      3.050      0.002       0.012       0.055
MS_P01          -0.4898      0.054     -9.056      0.000      -0.596      -0.384
VISBMINP         0.1237      0.073      1.692      0.091      -0.020       0.267
DDIS_FL          0.2750      0.054      5.138      0.000       0.170       0.380
GENDER2_2       -0.1661      0.054     -3.078      0.002      -0.272      -0.060
CTZSHIPP_2.0     0.0643      0.084      0.769      0.442      -0.100       0.228
CTZSHIPP_3.0     0.0186      0.116      0.161      0.872      -0.209       0.246
REG_INST_2       0.3091      0.082      3.747      0.000       0.147       0.471
REG_INST_3       0.1398      0.092      1.513      0.130      -0.041       0.321
REG_INST_4       0.3120      0.079      3.946      0.000       0.157       0.467
==============================================================================
Omnibus:                       114.134   Durbin-Watson:                   1.973
Prob(Omnibus):                   0.000   Jarque-Bera (JB):              105.041
Skew:                            0.476   Prob(JB):                     1.55e-23
Kurtosis:                        2.514   Cond. No.                         68.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

6.1 Analysis of NGS 2020 Data Using Linear Regression

6.1.1 Data Loading & Exploration

- **`pd.read_csv('ngs2020.csv')`**:
  Loads a CSV file named `ngs2020.csv` (likely survey data from the National Graduate Survey).
- **`df.head() & df.info()`**:
  Provides a quick look at the dataset structure (columns, data types, sample rows).

6.1.2 Data Cleaning

6.1.2.1 Handling Missing Values:

- Replaces common missing data codes (`6, 96, 99, 9`) with `NaN`.
- Drops rows with missing values (`dropna()`).

6.1.2.2 Target Variable:

- Assumes `'PERSINCP'` (likely personal income) is the variable to predict.

6.1.2.3 Predictor Variables:

- Includes demographic and socioeconomic factors like:
  - Gender (`GENDER2`)
  - Education (`EDU_010`)
  - Citizenship (`CTZSHIPP`)
  - ...and others.

6.1.3 Feature Engineering

6.1.3.1 One-Hot Encoding:

- Converts categorical variables (e.g., `GENDER2`, `CTZSHIPP`) into dummy variables using `pd.get_dummies()`.

6.1.3.2 Numeric Conversion:

- Ensures all data is numeric (`pd.to_numeric()`).
- Fills remaining missing values with column means.

6.1.4 Model Training & Evaluation

6.1.4.1 Train-Test Split:

- Splits data into training (80%) and testing (20%) sets.

6.1.4.2 Linear Regression (`sklearn`):

- Fits a linear regression model to predict income (`y`) from predictors (`X`).
- Evaluates using:
  - **R-squared** (goodness of fit).
  - **RMSE** (error magnitude).

6.1.4.3 Statsmodels OLS Regression:

- Provides a detailed statistical summary, including:
  - Coefficients.
  - P-values.
  - Confidence intervals.

6.1.5 Key Outputs

- **R-squared**:
  Indicates how well predictors explain income variation (e.g., `0.45` = 45% variance explained).
- **RMSE**:
  Measures average prediction error in income units.
- **OLS Summary**:
  Shows which predictors are statistically significant (e.g., `P > |t| < 0.05`).

7 Predict whether a student had a loan

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix



# Set style for visualizations
sns.set_style("whitegrid")
plt.rcParams['figure.figsize'] = (8, 18)

# Load the actual data
df = pd.read_csv('ngs2020.csv')

# Define missing value codes based on the data documentation
missing_codes = [6, 7, 8, 9, 96, 97, 98, 99]

# Create a function to visualize missing data
def plot_missing_data(df):
    missing = df.isin(missing_codes).mean() * 100
    missing = missing[missing > 0]
    missing.sort_values(inplace=True)

    plt.figure(figsize=(8, 12))
    missing.plot(kind='barh')
    plt.title('Percentage of Missing/Special Values by Column')
    plt.xlabel('Percentage (%)')
    plt.ylabel('Column Name')
```

```
    plt.show()

plot_missing_data(df)

# Data cleaning - replace missing codes with NaN
for col in df.columns:
    if df[col].dtype in ['int64', 'float64']:
        df[col] = df[col].replace(missing_codes, np.nan)

# Demographic Analysis
def demographic_analysis(df):
    print("\n=== Demographic Analysis ===\n")

    # Gender distribution
    if 'GENDER2' in df.columns:
        gender_mapping = {
            1: 'Men+',
            2: 'Women+',
            6: 'Valid skip',
            7: 'Don\'t know',
            8: 'Refusal',
            9: 'Not stated'
        }
        gender_dist = df['GENDER2'].map(gender_mapping).value_counts()
        print("Gender Distribution:")
        print(round(gender_dist),3)

        plt.figure(figsize=(5, 3))
        gender_dist.plot(kind='bar')
        plt.title('Gender Distribution')
        plt.ylabel('Percentage')
        plt.xlabel('Gender')
        plt.xticks(rotation=0)
        plt.show()

    # Visible minority status
    if 'VISBMINP' in df.columns:
        minority_mapping = {
            1: 'Yes',
            2: 'No',
            3: 'Not applicable',
            6: 'Valid skip',
```

```
            7: 'Don\'t know',
            8: 'Refusal',
            9: 'Not stated'
        }

        minority_dist = df['VISBMINP'].map(minority_mapping).value_counts()
        print("\nVisible Minority Status (%):")
        print(minority_dist)

        plt.figure(figsize=(5, 3))
        minority_dist.plot(kind='bar')
        plt.title('Visible Minority Status')
        plt.ylabel('Percentage')
        plt.xlabel('Visible Minority Status')
        plt.xticks(rotation=45)
        plt.show()

    # Age distribution (assuming GRADAGEP is age at graduation)
    if 'GRADAGEP' in df.columns:
        GRADAGEP_mapping = {
            1: '< 25',
            2: '25 to 29',
            3: '30 to 39',
            4: '>= 40',
            9: 'Not stated'
        }
        GRADAGEP_dis = df['GRADAGEP'].map(GRADAGEP_mapping).value_counts()

        print("\nAge at Graduation Distribution Summary:")
        print(GRADAGEP_dis)
        # print(round(df['GRADAGEP'].describe(), 3))

        plt.figure(figsize=(5, 3))
        GRADAGEP_dis.plot(kind='bar')
        # sns.histplot(df['GRADAGEP'].dropna(), bins=20, kde=True)
        plt.title('Age at Graduation Distribution')
        plt.xlabel('Age')
        plt.ylabel('Count')
        plt.xticks(rotation=45)
        plt.show()

demographic_analysis(df)
```

```
# Education Analysis
def education_analysis(df):
    print("\n=== Education Analysis ===\n")

    # Program level distribution
    if 'CERTLEVP' in df.columns:
        certlev_mapping = {
            1: 'College',
            2: 'Bachelor\'s',
            3: 'Master\'s/Doctorate',
            6: 'Valid skip',
            7: 'Don\'t know',
            8: 'Refusal',
            9: 'Not stated'
        }
        program_level = df['CERTLEVP'].map(certlev_mapping).value_counts(normalize=True) * 1
        print("Program Level Distribution (%):")
        print(program_level)

        plt.figure(figsize=(5, 3))
        program_level.plot(kind='bar')
        plt.title('Program Level Distribution')
        plt.ylabel('Percentage')
        plt.xlabel('Program Level')
        plt.xticks(rotation=45)
        plt.show()

    # Would choose same field of study again
    if 'PGM_430' in df.columns:
        field_choice_mapping = {
            1: 'Yes',
            2: 'No',
            6: 'Valid skip',
            7: 'Don\'t know',
            8: 'Refusal',
            9: 'Not stated'
        }
        plt.figure(figsize=(5, 3))
        field_choice = df['PGM_430'].map(field_choice_mapping).value_counts(normalize=True)
        print("\nWould Choose Same Field of Study Again (%):")
        print(field_choice)
        plt.title('Would Choose Same Field of Study Again')
```

```
        field_choice.plot(kind='bar')
        plt.xlabel('Would Choose Same Field of Study Again')
        plt.ylabel('Percentage')

        plt.xticks(rotation=45)
        plt.show()

education_analysis(df)

# Financial Analysis
def financial_analysis(df):
    print("\n=== Financial Analysis ===\n")

    # Student loan distribution
    if 'STULOANS' in df.columns:
        loans_mapping = {
            1: 'Yes',
            2: 'No',
            6: 'Valid skip',
            7: 'Don\'t know',
            8: 'Refusal',
            9: 'Not stated'
        }
        loans = df['STULOANS'].map(loans_mapping).value_counts(normalize=True) * 100
        print("Student Loan Distribution (%):")
        print(loans)

        plt.figure(figsize=(5, 3))
        loans.plot(kind='bar')
        plt.title('Student Loan Distribution')
        plt.xlabel('Student Loan')
        plt.ylabel('Percentage')
        plt.xticks(rotation=45)
        plt.show()

    # Personal income distribution
    if 'PERSINCP' in df.columns:
        # Convert to actual income values if possible
        # For now, just show the distribution of categories

        PERSINCP_mapping = {
            1: '< $30,000',
```

```
            2: '$30,000 to $49999',
            3: '$50,000 to $69,999',
            4: '$70,000 to$ 89,999',
            5: '$90,000 or more'
        }
        persincp_dist = df['PERSINCP'].map(PERSINCP_mapping).value_counts()
        print("\nPersonal Income Category Distribution (%):")
        print(persincp_dist)

        plt.figure(figsize=(5, 3))
        persincp_dist.plot(kind='bar')
        plt.title('Personal Income Category Distribution')
        plt.xlabel('Personal Income')
        plt.ylabel('Percentage')
        plt.xticks(rotation=45)
        plt.show()

financial_analysis(df)

# Employment Analysis
def employment_analysis(df):
    print("\n=== Employment Analysis ===\n")

    # Labor force status
    if 'LFSTATP' in df.columns:
        lfstat_mapping = {
            1: 'Employed',
            2: 'Unemployed',
            3: 'Not in labor force',
            6: 'Valid skip',
            7: 'Don\'t know',
            8: 'Refusal',
            9: 'Not stated'
        }
        labor_status = df['LFSTATP'].map(lfstat_mapping).value_counts(normalize=True) * 100
        print("Labor Force Status (%):")
        print(labor_status)

        plt.figure(figsize=(5, 3))
        labor_status.plot(kind='bar')
        plt.title('Labor Force Status')
        plt.xlabel('Labor Force Status')
```

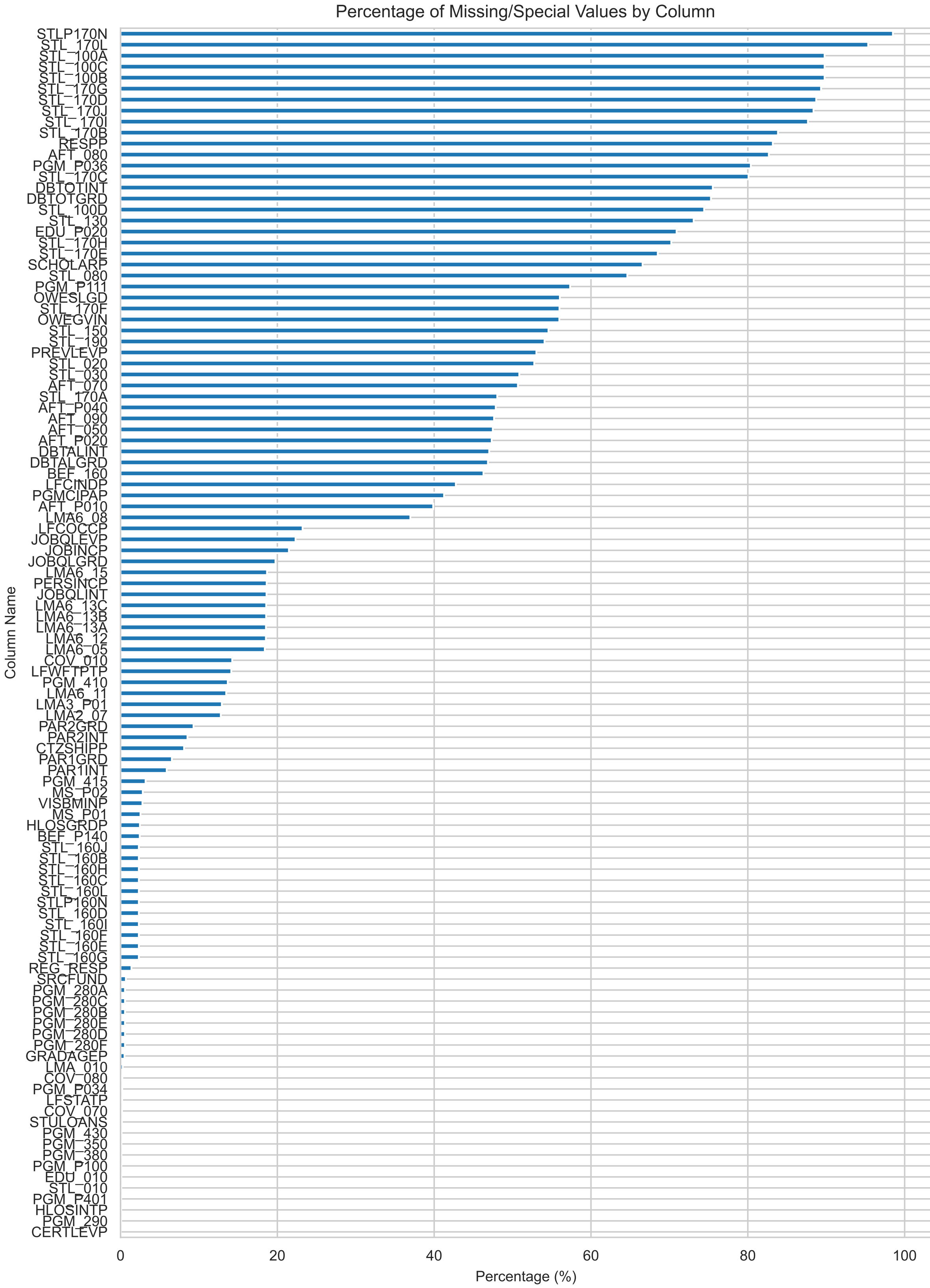
```
        plt.ylabel('Percentage')
        plt.xticks(rotation=45)
        plt.show()

    # Job income distribution
    if 'JOBINCP' in df.columns:
        # Convert to actual income values if possible
        # For now, just show the distribution of categories
        JOBINCP_mapping = {
            1: '< $30,000',
            2: '$30,000 to $49,999',
            3: '$50,000 to $69,999',
            4: '$70,000 to $89,999',
            5: '$90,000 or more',
            96: 'Validskip',
            99: 'Notstated'
        }
        job_income = df['JOBINCP'].map(JOBINCP_mapping).value_counts()
        print("\nJob Income Category Distribution (%):")
        print(job_income)

        plt.figure(figsize=(5, 3))
        job_income.plot(kind='bar')
        plt.title('Job Income Category Distribution')
        plt.xlabel('Job Income Category')
        plt.ylabel('Percentage')
        plt.xticks(rotation=45)
        plt.show()

    # Job-education relatedness
    if 'LMA6_11' in df.columns:
        relatedness_mapping = {
            1: 'Very related',
            2: 'Somewhat related',
            3: 'Not related',
            6: 'Valid skip',
            7: 'Don\'t know',
            8: 'Refusal',
            9: 'Not stated'
        }
        relatedness = df['LMA6_11'].map(relatedness_mapping).value_counts(normalize=True) *
        print("\nJob-Education Relatedness (%):")
```

```
        print(relatedness)

        plt.figure(figsize=(5, 3))
        relatedness.plot(kind='bar')
        plt.title('Job-Education Relatedness')
        plt.xlabel('Job-Education Relatedness')
        plt.ylabel('Percentage')
        plt.xticks(rotation=45)
        plt.show()

employment_analysis(df)

# COVID-19 Impact Analysis
def covid_analysis(df):
    print("\n=== COVID-19 Impact Analysis ===\n")

    # Program completion delayed
    if 'COV_010' in df.columns:
        delayed_mapping = {
            1: 'Yes',
            2: 'No',
            6: 'Valid skip',
            7: 'Don\'t know',
            8: 'Refusal',
            9: 'Not stated'
        }
        delayed = df['COV_010'].map(delayed_mapping).value_counts(normalize=True) * 100
        print("Program Completion Delayed Due to COVID-19 (%):")
        print(delayed)

        plt.figure(figsize=(5, 3))
        delayed.plot(kind='bar')
        plt.title('Program Completion Delayed Due to COVID-19')
        plt.xlabel('Program Completion Delayed Due to COVID-19')
        plt.ylabel('Percentage')
        plt.xticks(rotation=45)
        plt.show()

covid_analysis(df)


# Correlation Analysis
```

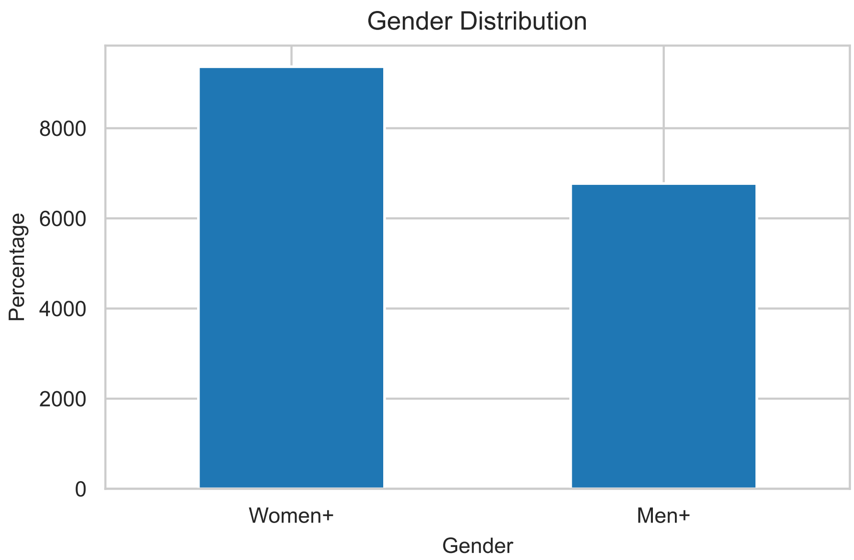
```
def correlation_analysis(df):
    print("\n=== Correlation Analysis ===\n")

    # Select columns that might have meaningful correlations
    corr_cols = [
        'GRADAGEP', #
        'PERSINCP', #
        'JOBINCP',  #
        'STULOANS', #
        'LFSTATP',  #
        'CERTLEVP'  #
    ]
    corr_df = df[corr_cols].copy()

    # Filter out missing codes
    for col in corr_cols:
        corr_df = corr_df[~corr_df[col].isin(missing_codes)]

    # Compute correlation matrix
    corr_matrix = corr_df.corr()

    # Plot heatmap
    plt.figure(figsize=(10, 7))
    heatmap = sns.heatmap(
        corr_matrix,
        annot=True,
        cmap='coolwarm',
        center=0,
        fmt=".2f"
    )
    plt.title('Correlation Matrix')
    heatmap.set_xticklabels(['age','personal income', 'job income','loan','job status','educ
    heatmap.set_yticklabels(['age','personal income', 'job income','loan','job status','educ

    heatmap.set_yticklabels(heatmap.get_yticklabels(),
                            rotation=90,
                            va='center')  # Vertical alignment center
    plt.show()

correlation_analysis(df)

# Predictive Modeling Example: Predict Student Loans
```

```
def predict_student_loans(df):
    print("\n=== Predictive Modeling: Student Loan Prediction ===\n")

    # Prepare data
    model_df = df[['GENDER2', 'CERTLEVP', 'PERSINCP', 'LFSTATP', 'STULOANS', 'GRADAGEP']].co
    model_df = model_df.dropna()

    # Filter out missing codes from the target variable
    model_df = model_df[model_df['STULOANS'].isin([1, 2])]

    # Convert categorical variables to numerical
    le = LabelEncoder()
    for col in ['GENDER2', 'CERTLEVP', 'PERSINCP', 'LFSTATP', 'STULOANS']:
        model_df[col] = le.fit_transform(model_df[col])

    # Split data
    X = model_df.drop('STULOANS', axis=1)
    y = model_df['STULOANS']
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42

    # Train model
    model = RandomForestClassifier(random_state=42)
    model.fit(X_train, y_train)

    # Evaluate
    y_pred = model.predict(X_test)
    print("Classification Report:")
    print(classification_report(y_test, y_pred))

    # Feature importance
    importance = pd.Series(model.feature_importances_, index=X.columns)
    importance = importance.sort_values(ascending=False)

    plt.figure(figsize=(5, 3))
    fig = importance.plot(kind='bar')
    plt.title('Feature Importance for Student Loan Prediction')
    plt.ylabel('Importance Score')
    fig.set_xticklabels(['personal income', 'age', 'education','job status', 'gender'])
    plt.xticks(rotation=45)
    plt.show()

# Only run if we have enough data
```

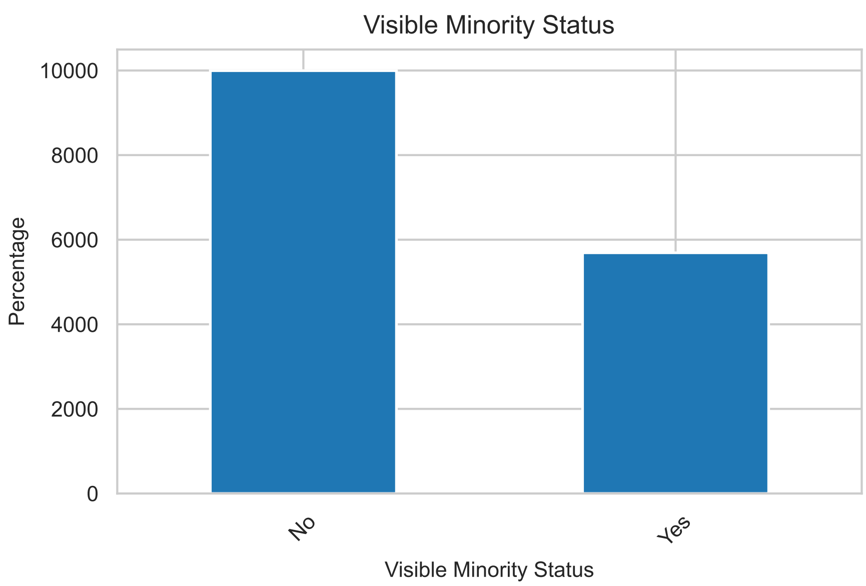
```
if len(df.dropna(subset=['STULOANS', 'GENDER2', 'CERTLEVP', 'PERSINCP', 'LFSTATP', 'GRADAGEP
    predict_student_loans(df)
else:
    print("Not enough complete data for predictive modeling example.")
```



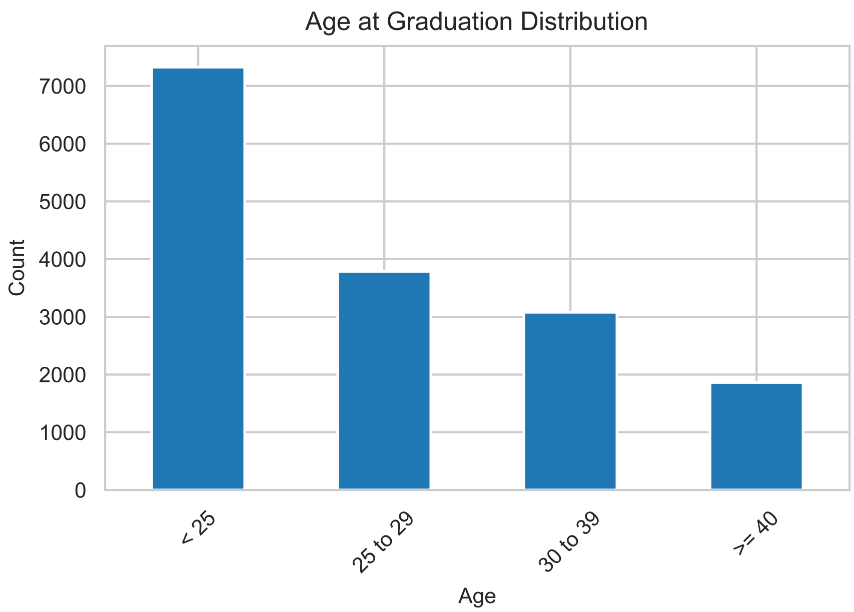
```
=== Demographic Analysis ===

Gender Distribution:
GENDER2
Women+    9365
Men+      6773
Name: count, dtype: int64 3
```



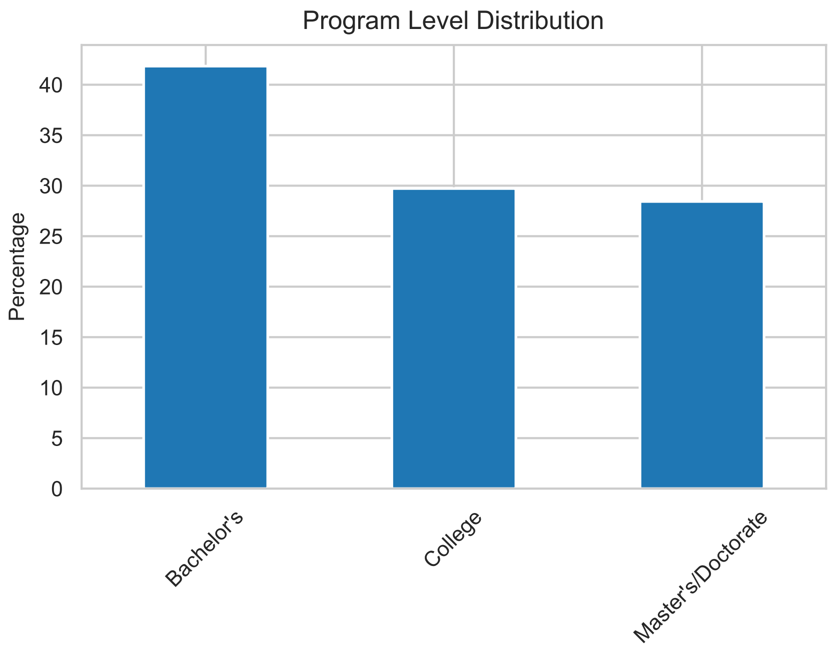

```
Visible Minority Status (%):
VISBMINP
No     9996
Yes    5691
Name: count, dtype: int64
```



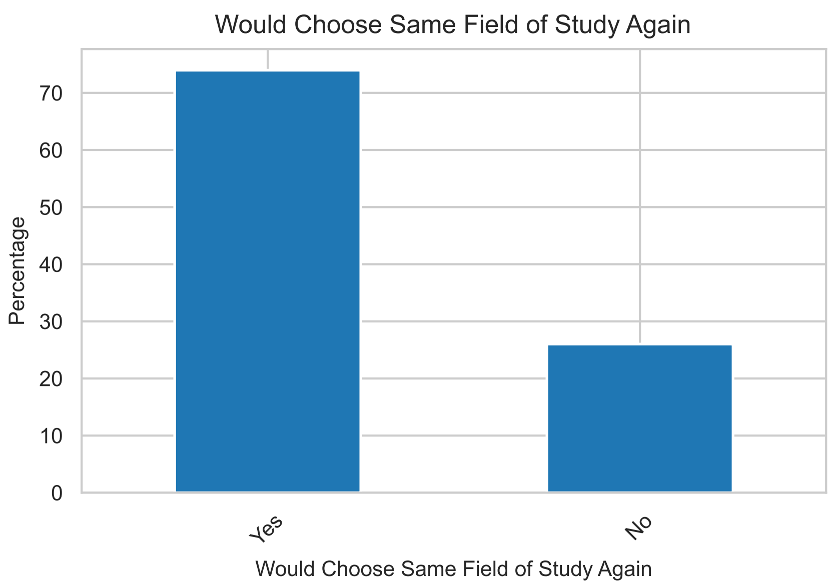
```
Age at Graduation Distribution Summary:
GRADAGEP
< 25        7326
25 to 29    3788
30 to 39    3079
>= 40       1863
Name: count, dtype: int64
```




```
=== Education Analysis ===

Program Level Distribution (%):
CERTLEVP
Bachelor's             41.841730
College                29.720518
Master's/Doctorate     28.437752
Name: proportion, dtype: float64
```

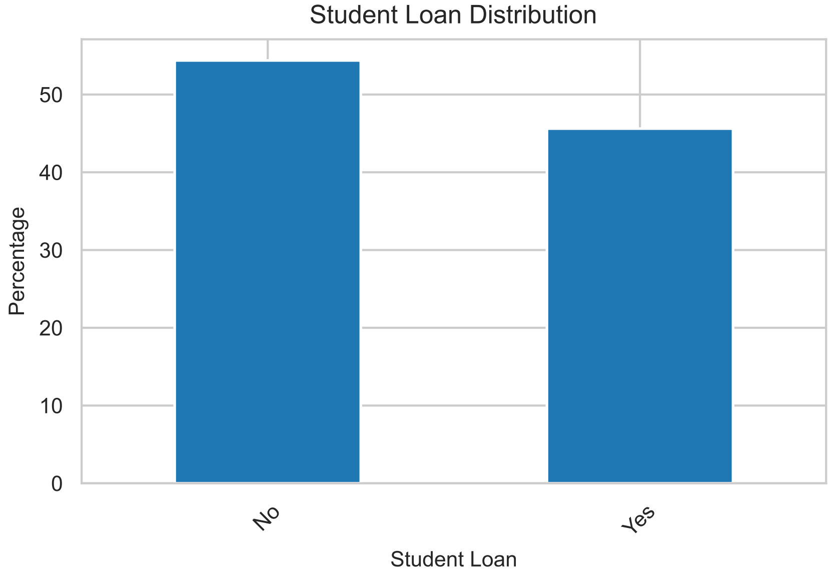



```
Would Choose Same Field of Study Again (%):
PGM_430
Yes     73.971583
No      26.028417
Name: proportion, dtype: float64
```

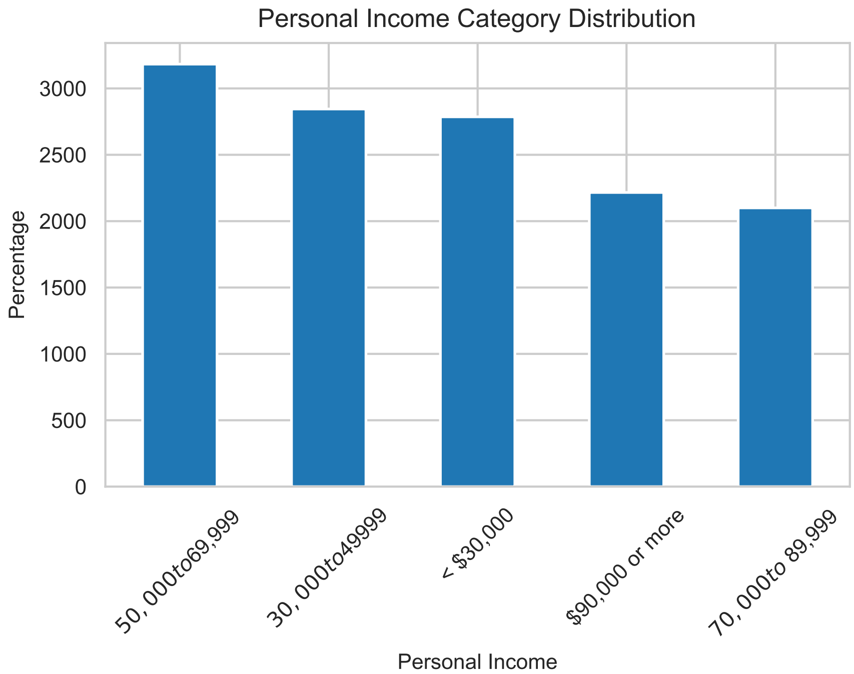



```
=== Financial Analysis ===

Student Loan Distribution (%):
STULOANS
No      54.382371
```

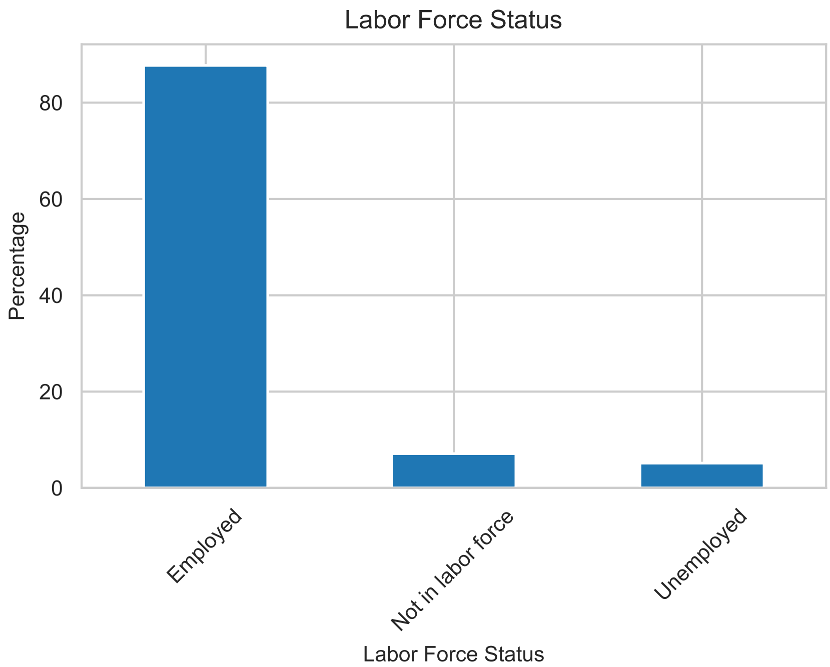
```
Yes    45.617629
Name: proportion, dtype: float64
```



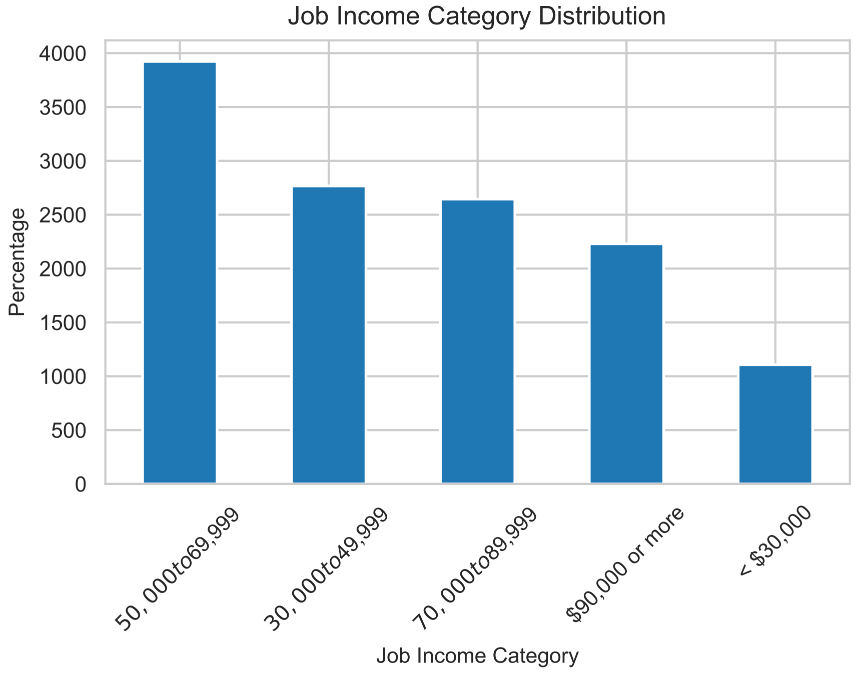

```
Personal Income Category Distribution (%):
PERSINCP
$50,000 to $69,999    3183
$30,000 to $49999     2845
< $30,000             2786
$90,000 or more       2216
$70,000 to$ 89,999    2100
Name: count, dtype: int64
```



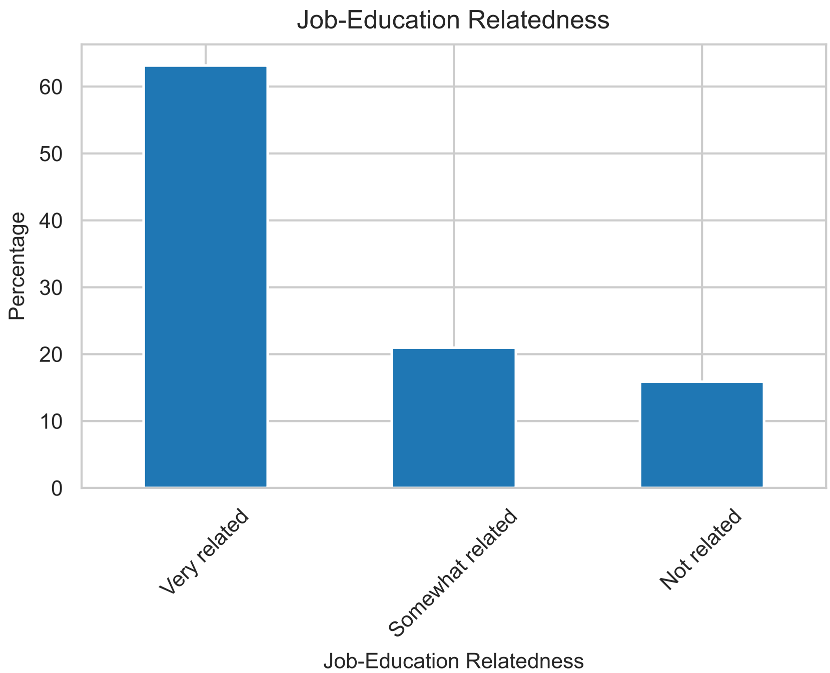
```
=== Employment Analysis ===

Labor Force Status (%):
LFSTATP
Employed               87.730518
Not in labor force      7.122012
Unemployed              5.147470
Name: proportion, dtype: float64
```




```
Job Income Category Distribution (%):
JOBINCP
$50,000 to $69,999    3923
$30,000 to $49,999    2767
$70,000 to $89,999    2645
$90,000 or more       2230
< $30,000             1107
Name: count, dtype: int64
```

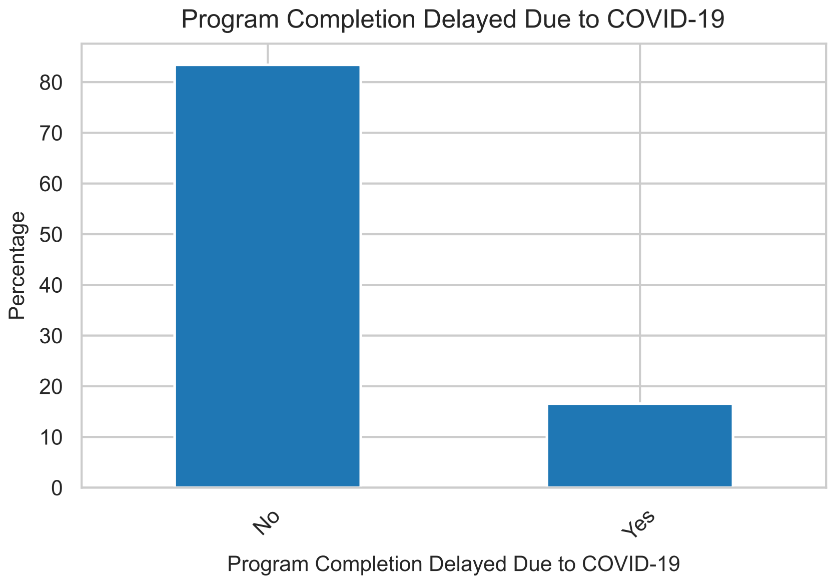



```
Job-Education Relatedness (%):
LMA6_11
Very related         63.145456
Somewhat related     20.969706
Not related          15.884839
Name: proportion, dtype: float64
```

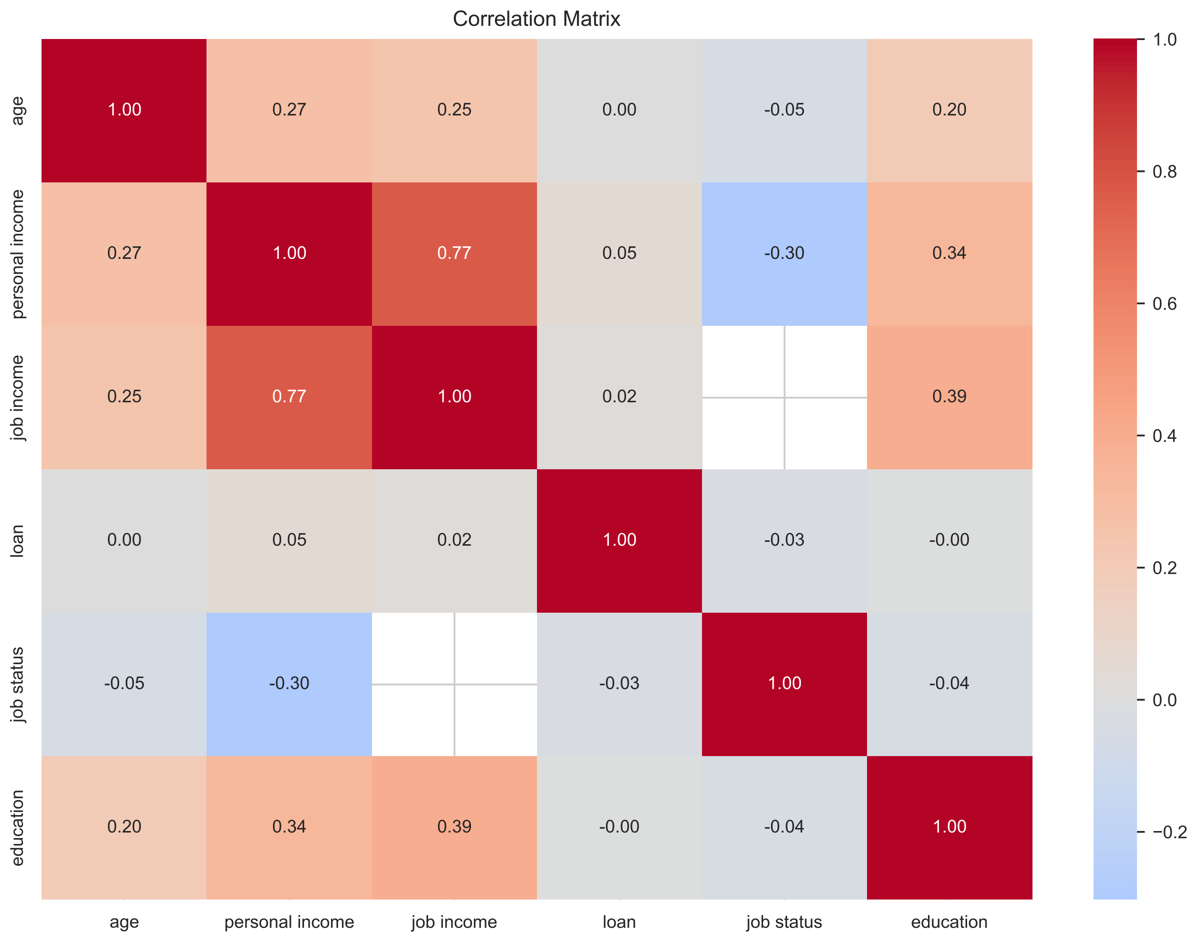



```
=== COVID-19 Impact Analysis ===
```

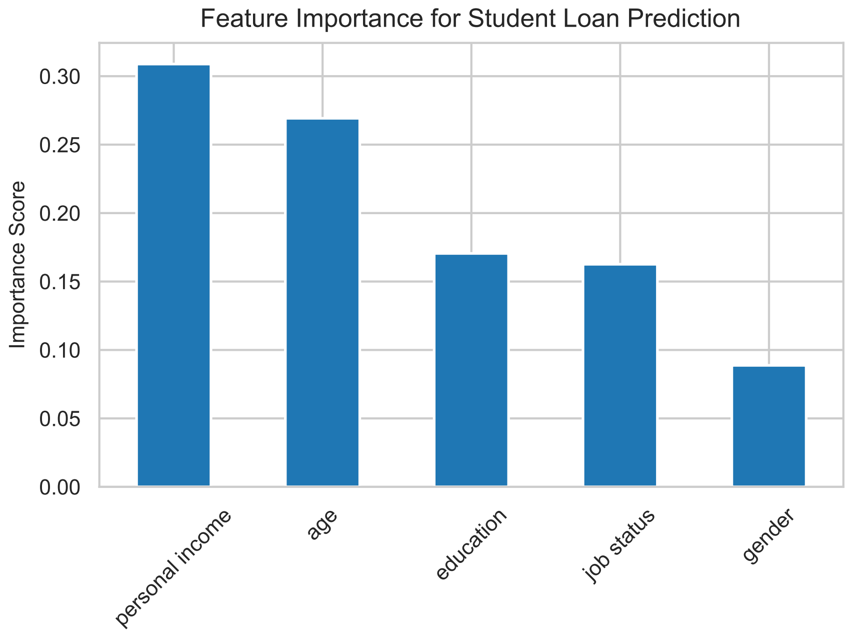
```
Program Completion Delayed Due to COVID-19 (%):
COV_010
No     83.416432
Yes    16.583568
Name: proportion, dtype: float64
```




```
=== Correlation Analysis ===
```



```
=== Predictive Modeling: Student Loan Prediction ===

Classification Report:
              precision    recall  f1-score   support

           0       0.53      0.39      0.45      1793
           1       0.58      0.70      0.63      2119

    accuracy                           0.56      3912
   macro avg       0.55      0.55      0.54      3912
weighted avg       0.55      0.56      0.55      3912
```



7.1 Setup & Initialization

- **Imports essential libraries**:
  - `pandas`, `numpy` for data manipulation
  - `matplotlib`, `seaborn` for visualizations
  - `scikit-learn` for machine learning
- **Sets visualization styles**:
  - Whitegrid background
  - 12x6 inch default figure size
- **Loads dataset**: `ngs2020.csv`

7.2 Data Preprocessing

- **Missing value handling**:
  - Defines special missing codes: `[6, 7, 8, 9, 96, 97, 98, 99]`
  - Visualizes missing data percentages by column

– Replaces missing codes with `NaN` for proper handling

7.3 Exploratory Data Analysis (EDA)

Demographic Analysis - **Gender distribution** (`GENDER2`) - **Visible minority status** (`VISBMINP`) - **Age at graduation** (`GRADAGEP`)

Education Analysis - **Program level distribution** (`CERTLEVP`): - College, Bachelor's, Master's/Doctorate - **Field satisfaction** (`PGM_430`): - "Would choose same field again?"

Financial Analysis - **Student loan prevalence** (`STULOANS`) - **Personal income distribution** (`PERSINCP`)

Employment Analysis - **Labor force status** (`LFSTATP`): - Employed/Unemployed/Not in labor force - **Job income** (`JOBINCP`) - **Job-education relatedness** (`LMA6_11`)

COVID-19 Impact Analysis - **Program delays** (`COV_010`): - "Completion delayed due to COVID?"

Analysis Methodology - Maps numeric codes → human-readable labels - Calculates percentage distributions - Generates visualizations: - Bar charts for categorical data - Histograms for continuous variables

7.4 Correlation Analysis

- **Key variables**:
  - Graduation age (`GRADAGEP`)
  - Personal income (`PERSINCP`)
  - Job income (`JOBINCP`)
  - Student loans (`STULOANS`)
  - Employment status (`LFSTATP`)
  - Education level (`CERTLEVP`)
- **Output**: Annotated correlation heatmap

7.5 Predictive Modeling

- **Goal**: Predict student loan status (`STULOANS`)
- **Features**:
  - Gender (`GENDER2`)
  - Education level (`CERTLEVP`)
  - Income (`PERSINCP`)
  - Employment status (`LFSTATP`)
  - Graduation age (`GRADAGEP`)
- **Workflow**:
  1. Filters/cleans relevant features
  2. Encodes categorical variables
  3. Trains Random Forest classifier
  4. Evaluates with classification report

5. Visualizes feature importance

- **Safeguard**: Only runs with sufficient complete data

7.6 Key Insights Generated

Demographic distributions: - Gender proportions - Minority representation - Age at graduation trends

Education patterns: - Program level distribution - Field of study satisfaction

Financial situations: - Student loan prevalence - Income bracket distributions

Employment outcomes: - Labor force participation - Income levels - Field relevance to education

Pandemic impacts: - COVID-related completion delays

Predictive relationships: - Feature importance for loan prediction

Inter-variable correlations: - Relationships between key metrics

8 Summary of the National Graduates Survey Analysis

The analysis of Canada's National Graduates Survey (Class of 2020) reveals critical insights about graduates' educational experiences, labor market outcomes, and socio-demographic characteristics:

- **Income Distribution**
  20.6% earned \$30,000-\$49,999 (most common bracket), while 18.2% earned \$50,000-\$69,999. Median income category was \$50,000-\$69,999.

- **Demographics**
  - **Age**: 54% graduated under 25; 77.2% under 30
  - **Gender**: Women+ (56.7%) outnumbered Men+ (43.3%)
  - **Citizenship**: 59.7% Canadian by birth, 14.4% naturalized citizens, 11.0% landed immigrants

- **Education**
  - 56.3% bachelor's degrees, 25.2% college diplomas, 18.5% graduate degrees
  - Top fields: Business (21.4%), Health (15.9%), Social Sciences (12.8%)

- **Geographic Mobility**
  - Ontario hosted 47.1% of institutions and 45.4% of graduates

- Western Canada saw net immigration (+1.4%); Atlantic provinces experienced outmigration (-0.4%)
- 68.3% remained in same region post-graduation

- **COVID-19 Impact**
  29.3% reported delayed completion; 33.6% had employment plans affected
- **Debt & Funding**
  60.6% used government loans; 55.2% relied on family support; Scholarships averaged $5,000-$9,999

9 Strategic Recommendations for Universities

9.1 Program Development and Delivery

- **Expand high-demand programs** in Business, Health, and STEM fields
- **Integrate mandatory work placements** (only 58.3% participated currently)
- **Scale online/hybrid delivery** (41.6% used distance education)

9.2 Enrollment and Marketing Strategy

- **Target mature learners** (22.4% of graduates were 30+)
- **Boost international recruitment** (11.0% were landed immigrants)
- **Develop regional retention programs** addressing outmigration

9.3 Student Financial Support

- **Increase mid-range scholarships** ($5,000-$9,999 range utilized by 20.9%)
- **Enhance debt counseling** for 23.9% owing >$25,000 at graduation

9.4 COVID-19 Response

- **Strengthen mental health services** for 29.3% reporting pandemic disruptions
- **Invest in digital infrastructure** for academic continuity

9.5 Career Development

- **Build regional employer partnerships** (68.3% stayed locally)
- **Implement salary negotiation training** addressing income disparities

10 Conclusion

The NGS 2020 data reveals three strategic imperatives for universities:

1. **Enhance program-market alignment** through responsive curriculum development in high-demand fields
2. **Address financial barriers** via targeted scholarships and debt management programs
3. **Strengthen regional ecosystems** by retaining talent and building industry partnerships

By prioritizing graduate employability, financial accessibility, and regional connectivity, universities will drive Canada's post-pandemic recovery while advancing equitable student outcomes. Strategic investments in these areas position institutions as engines of workforce development and social mobility.